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Striking Evidence?
Demand Persistence for Inter-City Buses from German Railway Strikes

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This paper investigates the effect of the largest rail strikes in German history in 2014-2015 on long-distance buses – a newly liberalized market. Using a novel dataset of detailed bus ticket sales and rail cancellations, I find that the primary channel that drives ticket sales during the strike is whether the absolute bus travel time was sufficiently short. In a difference-in-differences framework, I exploit this variation to identify any demand persistence. Although the common trend assumption does not seem to be completely tenable in the given context, my results point to a persistent effect on the ticket sales for inter-city buses on the affected routes.

JEL classifications: *L92, R41, C81*

Keywords: *Transportation, Long-Run Demand Effects, Intermodal Substitution, Strike*

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1 Introduction

1.1 Motivation and Outline

Does a temporary shock such as a strike boost one's competitors' demand? Can such shocks have lasting demand effects? I analyse these general questions in the context of the German railway strikes of 2014-2015. The strikes forced travellers to use alternative transport modes. For many travellers this was their first encounter with inter-city buses – a newly liberalized market.[1] Such a shock – in introducing new customers to the railway's key rival – has the potential to result in new, long-term customers for buses who otherwise would have routinely stayed with rail.[2] A German newspaper article suggested that *"the young bus market could benefit sustainably from the strike"*.[3] To the best of my knowledge, this study is the first to present systematic evidence of these qualitative accounts.

This chapter combines three novel and extremely rich datasets: detailed booking data provided by Germany's largest bus provider MeinFernbus (MFB), emergency timetables published by Deutsche Bahn (German Rail; hereafter referred to as DB) during the strikes, and a web-crawled dataset of all rail itineraries. Using this data, I study the adjustments of travellers to inter-city buses during the strike, and test for demand persistence. The German railway strikes of 2014-2015 provide several desirable features for a quasi-natural experiment setting. Competition from buses played no role in the exposure across routes, the occurrence, or the timing of the railway strikes. Furthermore, this was the first German railway strike in which buses – a viable alternative – were available.

My empirical strategy consists of two steps. Firstly, I test which routes were primarily affected *during* the rail strike. While the exposure of *rail routes* to the strike can be deduced from the emergency timetables, the exposure of *bus routes* is not ex-ante clear to the researcher. On the one hand, it is not clear how well travellers were informed about variations in DB service cancellations across routes.

[1] The market was liberalized by law as of January 2013. Previously the Passenger Transportation Act only permitted inter-city bus services if the state-owned railway company was unable to provide an acceptable service. Dürr et al. (2015) provide more details on the liberalization.

[2] Inter-city buses are defined as regularly scheduled services exceeding a distance of 50km. In the literature they are often interchangeably referred to as 'inter-urban' or 'long-distance' buses.

[3] Full relevant excerpt: *"(...) The young bus market could benefit sustainably from the strike. (...) Due to the strikes business travellers are compelled to try the bus and then use it again (...) The number of repeat bookings climbs."* (url: *http://www.faz.net/aktuell/wirtschaft/wer-vom-bahnstreik-profitiert-mietwagen-und-fernbusse-13603674.html*; 20/05/2015) Other anecdotal evidence is provided by Spiegel magazine who suggested that *"(...) the structural change will accelerate in the German domestic inter-city market."* (url: *http://www.spiegel.de/wirtschaft/service/bahn-streik-fernbus-unternehmen-profitieren-von-gdl-ausstand-a-1001003.html*; 05/11/2014)

On the other hand, travellers may only switch if the bus service is a close enough substitute to rail. I demonstrate that the only channel driving MFB ticket sales during the strikes is the closeness of substitution, measured by the bus travel time. Travellers switched to buses even on routes with little or no rail service cancellations. This suggests that they were not well informed about their exposure to the rail strike or had no trust in DB's ability to implement the emergency timetables. I show that the effect of the rail strikes was largest on routes with a short absolute bus travel time.

Secondly, I estimate the effects of the strikes on ticket sales *after* DB operations returned to normal; i.e. whether there was a persistent effect. In a difference-in-differences setting, I use the channel identified in the first step to define treatment and control group. More precisely, I compare the change in the number of customers between high (short bus travel time) and low (long bus travel time) strike-exposed routes. Although the common trend assumption does not seem to be completely tenable in the given context, my results point to a persistent effect on the ticket sales for inter-city buses on the affected routes. I follow the methodology of Nunn and Qian (2011), who employ a similar strategy in a different setting.[4] They estimate period-specific treatment effects for the *pre-period* in order to compare these to the post-treatment coefficients. Following their methodology, my results also remain largely unaltered to a number of alternative specifications and robustness checks.

This chapter proceeds as follows: The remainder of this section reviews the related literature and discusses several features of the railway strikes in 2014-2015. Section 2 introduces the datasets and provides new descriptive statistics on the inter-city bus market. Section 3 introduces potential transmission channels and tests which bus routes were most affected *during* the rail strike. Section 4 uses the results from the previous section to test for demand persistence *after* the strike. Section 5.2 reports robustness tests. Finally, Section 6 concludes.

1.2 Related Literature

The literature on the subject of rail strikes and their effects on traveller behaviour is surprisingly sparse. Bauernschuster et al. (2015) and Van Exel and Rietveld (2001) provide overviews. Often inference relies on survey data and the effect of the strike is studied retrospectively. While strikes

[4] Nunn and Qian (2011) study the impact of the introduction of the potato from the Americas on Old World population growth and urbanization.

occur on a regular basis, they are not easily anticipated and may not last long enough to formulate an appropriate research design. To the best of my knowledge, the only notable exception is Larcom et al. (2015), whose contribution is closely related to this chapter. They show that the 2014 London underground strike resulted in about 5 percent of commuters permanently changing their commuting route. They suggest that individuals under-experiment in normal times. Public transport strikes are often considered to be highly economically damaging (Kennan, 1986). Larcom et al. (2015) and this chapter highlight an unintended and potentially positive channel, which is often overlooked in the literature: if the rail strike revealed information, it may have been welfare improving. Some customers, who were forced to experiment with buses, discovered that their previous choice was not optimal.

This chapter contributes to this strand of the literature in two ways. Firstly, I study inter-modal switching across transport modes for inter-city transport – a less-frequent travel decision than daily commuting. The frequency of the travel decision might matter, as suggested by the behavioural economics literature on salience (Chetty et al., 2007). Secondly, in comparison to Larcom et al. (2015) the longer post-strike period allows me to better understand the short- and medium-term impacts of any effect.

This chapter supplements the classic literature relating to the way in which individuals decide between alternatives. There is a large and long-standing debate on rational decision-making (Weitzman, 1979; Morgan and Manning, 1985) and constraints such as search costs (Baumol and Quandt, 1964) or information asymmetries. My results cannot be reconciled with the classical economic assumption of perfectly informed and rational consumers. After all, bus services were available before the strikes and the availability of internet bookings – the primary booking channel – remedy some of the search costs. Porter (1991) argues that exogenous shocks may help individuals find their optimal choice by triggering a period of experimentation. The underlying idea of experimentation due to exogenously-imposed constraints, such as the non-availability of rail services, applies to the setting in this chapter.

Furthermore, learning could explain a permanent increase in demand for bus services. Travellers may learn about the service and quality of buses by actually testing and experiencing them. Foster et al. (2012) link the importance of consumer learning to plant growth. Alternatively, consumers may be pushed out of previous habits or update their beliefs on the relative quality of the two goods. In addition, they may have changed their perception about the reliability of rail, or they may have obtained new information from increased media coverage of inter-city buses during the strikes. Coates and Harrison (2005) find a negative impact of labour disputes over player salaries on future game attendance in Major League Baseball in the US. Their results point to additional potential mechanisms at play: retaliatory motives and damage to the brand. While related to my research question, the precise mechanism at work is a question for future research beyond the scope of this chapter. This chapter's main contribution is to show the demand effects on inter-city buses during the rail strike, and to test the effect's persistence.

Finally, this chapter is among the first of a small but growing body of literature which studies the German market for inter-city buses. The German market for buses was liberalized with the explicit intent of increasing inter-modal competition. New liberalizations are currently under consideration in several other European economies. Thus, the primary concern of this literature has been to study the impact of the market liberalization of German buses on rail ticket prices and services. Böckers et al. (2015) find that the effect on the DB network was larger at the periphery of the network.[5] Bataille and Steinmetz (2013) and Hirschhausen et al. (2008), provide theoretical models on the effect of the liberalization. These studies of inter-modal competition relate to a slightly older literature on the entry of low-cost airlines into Germany in the early 2000s (Friebel and Niffka, 2009). Dürr et al. (2015) study competition within the inter-city bus market, and estimate the price effect of a recent large merger of MeinFernbus and Flixbus.[6] Neither of these studies considers the effect of the recent German railway strikes. Further, the studies rely on data from online price comparison websites which usually provide few time-series observations. Given the uniqueness and level of detail of the booking dataset, the descriptives presented in this chapter contribute to a much improved insight into this young market and its dynamics.

1.3 The German railway strikes of 2014-2015

The locomotive drivers' union (Gewerkschaft Deutscher Lokomotivführer; hereafter referred to as GDL) is a relatively small but powerful union, and has a long history of disputes with DB. The 2014-2015 negotiations, however, constituted the most ferocious industrial action in the history of DB. Two factors contributed to the ferocity of the dispute: GDL was in a power struggle with a rival union, and new

[5]See also Evangelinos et al. (2015).

[6]See Gagnepain et al. (2011) for a more general review of bus market competition.

legislation was under review which threatened GDL's right to represent service personnel in future wage negotiations. Between September 2014 and May 2015 the dispute resulted in nine strike waves and 22 days affected by strikes – 354 hours of service disruptions. Because of the importance of the rail network to the economy, the dispute was followed extremely closely by both the German media and the public.[7]

In the 2014-2015 labour dispute, there were nine strike waves as specified in Table 1. I study the effects of the three major waves in 2014 (strikes 4-6; bold in Table 1), and disregard all strikes in 2015, because they coincide with the merger of MFB and rival competitor Flixbus in January 2015. In addition, I disregard minor warning strikes, as they only lasted a few hours and were announced with many days advance warning. My data suggest that the strikes were too short to have any measurable impact on the bus market. Customers could re-arrange their travel plans within the rail network at little cost.

Insert Table 1 and Figure 1 here

The 2014-2015 strikes display several desirable features for an ideal quasi-natural experiment. Firstly, the timing of the strikes was arguably exogenous. Strikes result from a breakdown of negotiations, the exact timing of which is unpredictable as negotiations often collapse quickly and unexpectedly. Once negotiations have broken down, the exact timing of a strike is still not clear. It could be delayed by days, weeks or months if the parties are hopeful of making progress or political pressure is exerted. The trade union centrally decides to go on strike after consulting its members. Importantly, there is no evidence to suggest that competition from buses played any role in the occurrence, timing or length of the strikes. The strikes can be considered an exogenous positive demand shock to the German bus market. Having reached a decision, GDL usually announced strikes at short notice to maximize their impact. Each strike was typically announced only two days in advance.[8] Delaying or rescheduling a trip in anticipation of a strike was not possible for the majority of travellers. Consumers were directly affected. Figure 1 provides a detailed timeline of the two distinct weeks in which the rail strikes took

[7] This chapter is concerned with passenger transport. Note, however, that the railway strikes affected both passenger and freight services by DB.

[8] In the empirical exercise, I drop the two departure days before and after each strike wave to remove any anticipatory effects (see Ashenfelter and Card, 1985). The descriptives presented in Section 2.2 suggest that anticipatory effects are negligible.

place, which I cover in this chapter. It outlines the short pre-announcement period before each wave and the length of the strike.

Secondly, GDL called for a strike nationwide. However, neither did GDL shut the network down entirely, nor were rail routes exposed to the same degree. GDL membership strength is weaker in West Germany, because many West German train drivers have civil servant status – a relic of DB's historical status as a state company.[9] The emergency timetables operated during the rail strike reflect the varying power of GDL across Germany. The change of service frequency specified in the emergency timetables was exogenous to the bus market: DB did not strategically focus rail services on routes which were under particular threat of competition from buses. The emergency timetables were the same in all strike waves in 2014-2015 and they are almost identical to those employed by DB in the last railway strikes of 2007-2008; i.e. long before the liberalization of the inter-city bus market in 2013.[10] Finally, DB made no attempt to employ locomotive drivers outside their usual geographic area of deployment for fear that they might be unable to return at the end of the day. While the exact rationale for offering some services over others is unclear, the geographic variation in strike exposure mirrors GDL membership, not the inter-city bus network. I discuss the transmission of the rail strike on bus routes in Section 3 below.

Thirdly, excluding those under focus, the last major rail strikes date back to 2007-2008, but the market for inter-city buses was not liberalized until 2013. In the 2014-2015 labour dispute, inter-city buses – a clearly defined rail substitute – were a viable alternative for the first time. Car and airline services were, of course, available in previous strikes. The inter-city bus market not only received substantial media coverage during the strikes but also attracted many travellers who had never travelled via inter-city buses before. For example, in an April 2014 survey prior to the strike, only 12 percent of young Germans indicated that they had used the newly available bus services (YouGov, 2014). Among older age groups this percentage is likely to be even lower because the trade-off in accepting longer travel times and less convenience for cheaper fares typically appeals to younger customers.

[9] German civil servants have by law no right to strike or unionise.

[10] A direct comparison of emergency timetables in 2007-2008 and 2014-2015 is difficult because normal DB timetables have changed substantially. However, *rail lines* have changed little. Over 60 percent of rail lines had nearly the same fraction of service cancellations in 2007-2008 and 2014-2015.

Fourthly, switching between rail and bus can be done quickly and easily.[11] Tickets can be bought through price comparison websites via the internet or on the bus. Furthermore, bus departure terminals are located directly next to the rail station in most cities (Guihéry, 2015). Travellers could arrive at the rail station and easily transfer to inter-city buses when the implications of the rail strike became clear to them.

2 Data and descriptive statistics

2.1 Data

This chapter combines three novel and extremely rich datasets: detailed booking data provided by MFB, DB emergency timetables, and a dataset of all rail itineraries. The latter dataset is collected using a web-crawler linked to the website of a leading price comparison website – a collection approach rarely used in the economics literature. I combine the emergency timetables and travel itineraries to create a dataset of service cancellations and expected delays caused by the rail strike. I summarize key features of the data below. Given the novelty of the data, I document additional information on the construction of all variables in Appendix 6.1.

MeinFernbus booking data

MFB is Germany's largest bus provider with a market share of roughly 50 percent during the sample period. In addition to being the key player in the German inter-city bus market, MFB's service quality as well as strategic use of local bus partners are representative of the entire inter-city bus industry.[12]

The dataset provided by MFB contains the universe of MFB ticket sales between any combination of 33 large German cities for departure dates from September 01^{st} to December 31^{st} 2014. Individuals who departed in the sample period, but who booked their ticket outside the sample period are also

[11] DB does not offer season passes on specific routes. It offers the *BahnCard* which grants fixed price reductions to card holders. *BahnCard* subscriptions can be cancelled annually. This may have locked travellers in to the services of DB, in which case any lasting effect beyond the strike would not be visible until the medium or long-term.

[12] For example, free internet, luggage allowance, and leg-room are almost identical across the industry. See Dürr et al. (2015) for detailed introduction and comparison of players in the inter-city bus market.

included. The original dataset contains about 1.7 million individual bookings. A booking observation includes detailed information on the bus service such as the route, price, departure date and time as well as information on the individual in form of an anonymized e-mail address. The e-mail address identifies first-time and repeat bookings by an individual, and thus allows following a customer over time.

The key variable of interest is the natural logarithm of the number of tickets sold at the route and departure day level.[13] Thus, I aggregate the individual bookings at the route and departure day level – the unit of analysis in this paper.[14] A route is the combination of an origin- and destination- city, so different routes may be served by the same bus journey. For example, a bus ride from Munich to Berlin with a stop in Dresden serves three routes: Munich–Dresden, Munich–Berlin and Dresden–Berlin. I treat each route as an independent and separate market. This has the advantage that it captures travellers such as commuters who repeatedly travel. For these people I can calculate their precise exposure to the rail strikes. The drawback is that this definition does not capture travellers who return after the strike but travel on a different route.[15]

While rail strikes continued beyond the sample period to May 2015, I restrict the sample period to 2014. This is because MFB unexpectedly merged with rival bus provider Flixbus in January 2015. Any changes after this date may be driven by the effects of the merger and not the rail strike.

Figure 2 lists and maps all 33 cities in the sample. However, not all route combinations are served. Inter-city buses are not legally permitted to connect cities at less than 100km distance or where local train travel time does not exceed one hour. Some routes are only served on some weekdays or not served at all. I employ a strict definition of which routes to include in the dataset: I drop those routes on which the number of days in the sample in which no customer travels that route exceeds ten. I confirm that my results are not sensitive to this cutoff. Cutting the dataset in this way represents a

[13] The dependent variable is computed as ln(1+tickets sold) at the route departure day level. This approach is common in the trade literature, and allows me to keep route-day observations with zero tickets sold (see Felbermayr and Kohler, 2006). In the dataset, zero observations only account for 0.3 percent of tickets sold and 7 percent of tickets sold to new customers. I confirm that my results are unaltered if I drop all zero observations.

[14] For clarity note that there are two time dimensions to each individual booking: the date of the booking and the date of the departure. I aggregate ticket sales to the route and departure date dimension. 95 percent of bus travellers arrive on the same date as they depart.

[15] In the later difference-in-differences analysis, strike-exposed customers, who return on a different (non-treated) route in later journeys, would bias the estimated effect downwards. Thus, the estimated effect could be interpreted as a lower bound to the true effect.

trade-off between clarity and statistical power. Given the size of the dataset, however, this is not a major problem.

Insert Figure 2 here

The final panel contains a cross-section of 312 routes and roughly 34,000 observations at the route and departure day level. The dataset is balanced in the sense that all routes are observed over the entire sample period and through all strike waves.

DB Emergency timetables and web-crawled itineraries

In addition to the MFB booking data, I construct a dataset of DB service cancellations and expected delays for each route during the rail strikes. This dataset combines emergency timetables provided by DB during the strikes and a dataset of all DB travel itineraries, which was collected using a web-crawler linked to the website of a leading price comparison website. The former provide data on normal frequency and the frequency during the strikes of all rail lines. The latter dataset includes all travel itineraries for the routes of the dataset during a complete week. A travel itinerary is defined as the specific departure times, stopovers and train numbers a traveller needs to take on a rail journey.

The DB emergency timetables list DB services at the *line level*. For example, ICE line 25 from Hamburg to Munich halved its operations from once every hour to once every two hours. However, actual travel itineraries are much more complex and often involve stopovers. A typical itinerary involves the use of multiple rail lines. Using actual itineraries takes into account that some DB routes are served through different paths in the rail network. Only the combination of emergency timetables and the travel itineraries allows me to construct the average exposure of each route to the rail strike. One data limitation remains, however: the DB emergency timetables do not include information on regional trains. I disregard routes where more than 10 percent of itineraries include the use of regional trains. This is not a major problem. Since the data focus on connections between the largest German cities, most itineraries include inter-city lines only.

Insert Figure 3 here

To measure each route's exposure to the rail strike, I construct two variables: the fraction of cancelled rail departures during the strikes (*fraction services cancelled*) and the expected time delay (*additional* *travel time*). The expected additional travel time travellers have to incur to reach their destination is calculated as the time a traveller has to wait for the next train if their service is cancelled. On the one hand, this measure takes into account the typical stopovers involved on each route. On the other hand, I neither observe delays in the travel time due to unexpected stopovers, nor delays due to unexpected additional halts. Furthermore, actual waiting times may have differed substantially depending on the actual arrival of travellers at the rail station, which is unobserved. However, defining additional travel time in this way has the advantage that it mirrors the structure of the emergency timetables, the primary source of information available to customers. Figure 3 plots the rail travel time in normal times against the additional travel time (Panel A) and the fraction of rail services cancelled (Panel B) for all routes. The routes Berlin–Munich and Hamburg–Berlin highlight the difference between the two measures. While both routes had almost identical service cancellations (about 75 percent), the time a customer had to wait for the next train was much longer for Berlin–Munich. This is because Hamburg–Berlin operated at a much higher frequency even in times of the strike. In addition, note that there is no visible systematic relationship between rail travel time and the strike-exposure measures.

2.2 Descriptive statistics

Before turning to the econometric analysis, I present some descriptive statistics. Given the novelty and level of detail of the dataset, they may be of more general interest. Additionally they highlight some important features of the data and clarify some selection choices I make for the empirical regression exercise below.

Figure 4 presents aggregate changes to MFB services over the sample period. For ease of interpretation I report weekly data.[16] Panel 1 plots the key variable of interest *ln ticket sales* for each departure. Sales peak during each strike wave as well as on national holidays such as October 3rd which in 2014 fell on a Friday, thus creating a long weekend. As expected, the increase in ticket sales is particularly pronounced for first-time customers (Panel 2). Panels 3-6 plot supply related descriptive statistics. Panels 3 and 4 display the negative trend in total capacity and departures over the sample period, reflecting the seasonality of public transport demand. Demand is weaker in winter and MFB reduced

[16] Ticket sales on Friday and Sunday exceed weekday sales on Tuesdays and Wednesdays by a factor of almost two. Share of ticket sales per weekday for the dataset: Monday 13%, Tuesday 10%, Wednesday 10%, Thursday 12%, Friday 19%, Saturday 15%, Sunday 20%.

the frequencies of its services, especially on off-peak weekdays. Panel 4 indicates that MFB, despite the short time-frame of each strike announcement, was able to increase its capacity during the rail strikes. Panels 5 and 6 address the capacity utilization of MFB.[17] A concern might be that customers were not able to switch to inter-city buses during the rail strikes, because buses were operating at full capacity. If so, the number of people exposed to inter-city buses would be much lower, and the estimated effect on bus ticket sales should be considered a lower bound. As indicated in Panels 5 and 6 MFB buses have additional tickets available in more than 80 percent of departures. This fraction does not increase substantially during the rail strike. Even if customers were faced with a fully-booked bus during the strike, there is a high probability that they could have successfully bought a ticket on the next bus.

The key takeaways from Figure 4 are twofold. Firstly, MFB ticket sales data display seasonality. To make sense of the effect of the strike, it is important to have an appropriate control group in the empirical analysis. Secondly, I drop the final two weeks of observations. Figure 5 displays how exceptional the Christmas travel period is. I do not want this seasonal shock to obscure my results. Cutting the dataset in this way represents a trade-off between clarity and statistical power. Given the size of my dataset, this is not a major problem. The remaining 36 post-strike departure days allow me to estimate the short- and medium-run effects of the rail strike.

Insert Figure 4 and Figure 5 here

Figure 5 splits ticket sales into returning and new customers. The figure suggests the positive effect of the rail strikes on ticket sales during each strike wave. Sales during the strikes were almost exclusively driven by customers who had never previously travelled by inter-city buses. On average, 30 percent of bus passengers are first-time customers, and two thirds of these undertake at least one more booking in the future.

An additional concern may be that customers switched to buses for reasons unrelated to the strike. While my regression analysis controls for unobservable effects with fixed effects and indicators for observable events such as school holidays, there may have been unobserved parallel events that drove

[17]Because a bus has multiple stops, the remaining capacity for each route does not correspond to the number of ticket sold for that route. For example, a bus that travels from Munich to Berlin via Dresden with 50 seats may be at capacity between Dresden and Berlin if 30 tickets were sold from Munich to Berlin and 20 from Dresden to Berlin. To address this issue, Panels 5 and 6 plot the bottleneck capacity: the remaining capacity for the section of the bus trip where the bus was most full.

bus ticket sales during the rail strikes. To address this concern, Figure 6 compares cumulative bookings prior to departure for a day affected by railway strike with a typical booking curve. The dashed vertical line indicates the moment of the strike announcement for the third strike wave on November 07, 2014.[18] As is apparent, ticket sales only diverge from their usual trend after the rail strike was announced. The small sales departure from the usual trend before the announcement suggests that a few travellers booked bus tickets after negotiations had broken down, but before the strike was announced; i.e. very few travellers anticipated the strike. If travellers booked tickets for buses for departure days before the strike in anticipation, my results would be downward biased. While I cannot observe whether new bus customers switched from the railway, Figure 6 provides strong descriptive evidence that it was the rail strikes that drove the peak in ticket sales on the striking days.

Insert Figure 6 here

3 Impact during the strike

3.1 Potential transmission channels

While the exposure of *rail routes* to the strikes can be deduced from the emergency timetables, the exposure of *bus routes* is not ex-ante clear to the researcher. In an ideal natural experiment rail and bus would be perfect substitutes, and customers would be perfectly informed about the exposure of their proposed route to the strike. They would experiment with buses only if affected by the strikes, and if inter-city buses were a reasonably attractive alternative. However, bus and rail services are neither perfect substitutes nor were customers perfectly informed about each route's exposure to the strike.

Thus, this section tests three potential channels that could determine the variation in exposure of the strike on inter-city buses *during* the rail strikes, and consequently the definition of the treatment group.

The transmission channels can be broadly categorized as follows. Firstly, bus and rail services are not perfect substitutes. The quality of bus and rail services differs both in observable characteristics, such

[18]See week B of Figure 1.

as travel time, as well as unobservable characteristics, such as comfort. Relative and absolute travel time matter. For example, a trip from Hamburg to Berlin takes two hours by rail and three hours by bus while a trip from Munich to Berlin takes about six hours by rail, and only one hour more by bus despite the longer absolute travel time. It is unlikely that many travellers would have opted to take the bus on routes where the bus travel time significantly exceeds that of the railway. Instead, they may have simply cancelled their trip or opted for other transport modes such as cars or aircraft. Another quality characteristic is comfort. Despite offering free internet access, the comfort of travelling by bus is generally regarded to be lower than rail travel. In this case consumers may value additional travel time in a bus differently to additional travel time by rail. They may be unwilling to take the bus above a certain threshold travel time. Finally, bus and rail services differ in price. Buses are generally cheaper than DB services. It follows that it is unlikely that customers weren't able to afford to switch during the strike. Travellers, who had booked a rail ticket, could demand a refund during the strikes even if some later trains were available.

Secondly, travellers were not perfectly informed about emergency timetables and their exposure to the strike. They may have struggled to obtain the relevant information about their personal exposure to the rail strike. In addition to publishing detailed emergency timetables, DB operated a free hotline for customers. Given that rail strikes were announced with little notice, most travellers are likely to have purchased their ticket previously. Thus, they had strong incentives to inform themselves about delays and service cancellations relevant to their itinerary. However, it is unclear whether they were able to do so. It is indeed possible that travellers on all routes considered themselves to be affected by the strike. There is some anecdotal newspaper evidence which confirms this suspicion. It reports that some of the railways in operation during the strikes – instead of being overcrowded – were emptier than usual.[19] Moreover, travellers may not have trusted DB's ability to successfully implemented its emergency timetables. The ability to implement the emergency timetables often depended on the exact number of train drivers that would turn up (or not) on the strike day – the precise number of which was often uncertain until the last minute.

Thirdly, the effect of the strike on MFB ticket sales may be the result of a combination of service cancellations from the strikes and the closeness of substitution between the transport modes. Travellers

[19]Source: manager-magazine (url: *http://www.manager-magazin.de/lifestyle/artikel/jeder-zweite-gueterzug-und-jeder-dritte-personenzug-faehrt-a-1001657.html*; 07/11/2014)

may have switched to inter-city buses if their itinerary was significantly affected *and* inter-city buses were a sufficiently attractive alternative to DB services on their route.

Since it is not ex-ante clear which routes were affected during the rail strike, and which were not, I test each of these three potential transmission channels using a number of proxy variables specified below.

3.2 Specification

I restrict the dataset in three ways. Firstly, since the focus of this section is on the effect during the strike, I disregard the post-strike period so as not to condition results on post-strike outcomes. Secondly, I restrict the data to focus on ticket sales to first-time customers that booked in the final three days to departure.[20] This decision uses the level of detail of the MFB booking data and is motivated by the findings in the descriptives section: ticket sales to new customers give a clearer indication of the transmission channel during the strikes. Further, strike-related bookings occurred primarily in the final days before departure; i.e. after GDL announced the precise timing of the strike. Thirdly, I disregard all ticket sales for departures two days before and after each strike. As outlined in Figure 1, there may be anticipatory effects and lagged treatments as DB services require time to return to normal operations. In addition, I disregard the intermediate fortnight between the second and third strike wave. It is not clear whether there would be a treatment effect between the strike waves in my sample.

My baseline regression takes the following form:

$$\text{ln ticket sales}^{\text{new}}_{ijt} \; = \alpha_{ij} \; + \; \tau_t \; + \; X_{it} \; + \; X_{jt} \; + \delta \, (\text{channel}_{ij} \times \text{strike}_t) \; + \; \epsilon_{ijt} \tag{1}$$

where ij refers to a route from origin-city i to destination-city j, and t to the departure day. The dependent variable $\textit{ln ticket sales}^{new}_{ijt}$ is defined as the log of tickets sold to new customers in the final three days to departure. α_{ij} and τ_t are route and departure day specific fixed effects respectively. The route fixed effects capture observed and unobserved differences that are constant over time such as dis-

[20]Note that there are two time dimensions to each booking observation: the date of the booking and the date of the departure. Here I aggregate ticket sales to the route and departure date dimension if the ticket was booked in the final three days to departure. As outlined in Figure 6 this primarily captures booking after the announcement of the strikes by GDL.

tance. The time fixed effects capture the effects of observed and unobserved temporal factors common to all routes such as national holidays, MFB marketing campaigns, or seasonal fluctuations.

X_{it} and X_{jt} are vectors of city-departure date specific control variables: A dummy for public holidays, school holidays and dummies for other major events.[21] I list all control variables used in the regressions in Table 2. Each control variable is interacted with month and weekday indicators to capture more variation in the data. Finally, the specifications with controls include origin- and destination- specific linear time trends.

In an additional specification, I include origin- and destination- departure day specific fixed effects, denoted γ_{it} and γ_{jt} respectively.[22] This is my preferred specification. Note that the inclusion of these route-specific fixed effects nests a complete set of origin and destination specific fixed effects. Furthermore, these strong fixed effects make the inclusion of the departure day fixed effects and the control variables redundant.

ϵ_{ijt} is the error term. Using a difference-in-differences strategy with many years, I have to worry about serial correlation at the group level. Conventional standard errors may severely understate the true standard errors (Bertrand et al., 2004). To address potential serial correlation within routes and time correlation, I cluster standard errors by route throughout the paper.

$(channel_{ij} \times strike_t)$ is the interaction term of interest. On the one hand, $strike_t$ is a vector of indicators for each strike wave studied in this chapter. As discussed in the background section, I disregard minor warning strikes, as they only lasted a few hours and were announced with many days advance warning. Any impact of these earlier warning strikes would bias my results downward. On the other hand, $channel_{ij}$ captures the different potential transmission channels.

To capture the effect of each potential transmission channel, I use proxy variables as follows. Firstly, I proxy the degree to which rail and bus services are substitutes using three variables: the *relative travel time difference* between rail and bus, *absolute travel time difference*, and *bus travel time*. Panels 1 and 2 of Figure 7 show that routes with a short bus travel time also show a small absolute bus travel time difference; i.e. both variables are strongly correlated. Thus, bus travel time captures the

[21]Note that German school holidays vary at the state level. Thus, school holidays are not captured by the departure day fixed effects. Source: schulferien.org

[22]Note that the inclusion of origin-day and destination-day fixed effects mirrors the fixed effects typically used in the estimation of gravity trade models to address 'multilateral resistance' terms (Anderson and van Wincoop, 2003).

likelihood that, even if the absolute travel time difference is small, travellers regard buses as sufficiently comfortable only for bus routes below a certain threshold travel time.

Secondly, I measure the strike exposure using the two variables constructed from DB emergency timetables in the data section: the *fraction of services cancelled* and *additional travel time* that customers had to endure to reach their destination during the strikes. The latter explicitly takes into account the fact that some routes operated at a much higher frequency even in times of the strike.

Thirdly, both the closeness of substitution and the exposure to the rail strike could be the primary factors driving bus ticket sales during the strike. To capture this channel, I estimate a set of regressions with a triple interaction between the proxies of the above channels. The triple interaction takes the following form: $(channel^{sub}_{ij} \times channel^{exp}_{ij} \times strike_t)$, where $channel^{sub}$ are the variables from the substitution channel (*relative travel time*, *absolute travel time* and *bus travel time*), and $channel^{exp}$ includes the exposure channel variables (*fraction services cancelled* and *additional travel time*). This specification also includes the first-order interaction terms to distinguish the triple interaction term. Note that Equation 1 does not include the lower-order terms as they are captured by the route and departure day fixed effects.

I repeat separate regressions for each proxy variable. Moreover, I estimate each channel variable as a dummy indicating whether it is above/below the median value. This is to ease interpretation and to make the estimated regression coefficients for each proxy more easily comparable. Thus, the dummies for *relative travel time*, *absolute travel time* and *bus travel time* equal one if the route is shorter than the median. Likewise, the dummies for *fraction services cancelled* and *additional travel time* equal one if the fraction of cancellations or travel delay exceed the median value respectively. In the robustness section, I confirm that my results are unaltered to using continuous definitions for the treatment variables.

Insert Figure 7 and Table 2 here

Figure 7 displays how each channel variable divides routes into treatment and control. Routes are of course not clearly divided into treatment and control, but treatment is imprecise. A route which is classified as above the median for one of the channel variables is best thought of as being 'more treated' relative to a route below the median. Defining the treatment channel in this way has the drawback that my measure includes a number of 'false negatives' and leads to type II errors. Fricke (2015) demonstrates that in this case the estimated result will be biased downwards and could be interpreted as a lower bound to the true effect. Finally, Table 2 presents basic summary statistics (including the median) for the set of explanatory variables. In addition, Table 9 in Appendix 6.1 provides specific definitions of all variables estimated in Equations 1 to 6.

3.3 Results

Having employed this extensive combination of fixed effects and controls, the coefficient of interest indicates whether routes that were below (above) the median for one of the proposed channels differ significantly compared to routes above (below) the median. In total, I estimate Equation 1 in eleven regressions: a regression for each of the different proxy channel variables introduced above and triple interactions between the combination of closeness of substitution and exposure to rail strike proxies. Table 3 summarizes all regression results.

Insert Table 3 here

Based on the three transmission channels outlined above, I find no evidence for the exposure channel. The proxy variables measuring this channel, *additional travel time* and *fraction services cancelled*, yield no robust statistically significant effects during the strike. I do not find evidence for the third channel, the combination of exposure and closeness of substitution, either. None of the triple interaction terms between the proxies yield robust statistically significant coefficients. I move the regression tables 10-18 to Appendix 6.2 for space concerns. See rows 3-11 in Table 3 for a summary.

Table 5 reports the regression results for the proxy variable *absolute travel time difference* and Table 4 the results for the variable *bus travel time*. They are the only two channel variables which yield consistently robust and statistically significant coefficients. Thus, my results suggest that the primary channel driving MFB ticket sales during the strikes was the closeness of substitution as measured by the proxy variables *absolute travel time difference* and *absolute bus travel time*. This is surprising as it suggests that travellers switched to buses even on routes with little or no service cancellations. It follows that either they were not well informed about their exposure to the rail strike, or had no trust in DB's ability to implement the emergency timetables.

As indicated in Figure 7 above, both *bus travel time* and *absolute travel time difference* are strongly correlated. One proxy variable may capture the effect of the other. Thus, I run an additional specification including both proxies simultaneously. This addresses whether travellers mainly disliked long bus travel times, or primarily cared about the travel time difference of the bus relative to rail, or both. Table 6 reports the results. I find that the absolute travel time difference proxy variable has no significant explanatory power in explaining ticket sales during the rail strikes once I control for the bus travel time. Thus, the primary factor explaining increased ticket sales for inter-city buses during the strikes is the length of the ride.

The magnitude of the effect during the strikes is large, but in line with expectations. Table 4 predicts that ticket sales to new customers in the final three days to the average route below the median bus travel time exceed ticket sales to the average route above the median by almost 50% in the third strike wave (column 1). The magnitude is similar but smaller for the other columns. As expected strike wave 1 yields the smallest coefficients as it fell on a Wednesday. Strike waves 2 and 3 fell on a weekend, whereby strike wave 3 was a longer strike.

Before using these findings to test whether the rail strike had an effect beyond the duration of the strike, I provide an additional test to confirm the results. I re-run the regression with *bus travel time* splitting the variable into 3-hour bins. The results are reported in Table 7. The table confirms the earlier result: the closer the substitution between bus and rail, the larger the effect during the rail strike. Column 1 of Table 7 suggests that routes connecting cities with a travel time below three hours observed almost twice as many bookings in the third strike wave than the longest routes in the sample. The estimated coefficients are similar in columns 2-4, where I include control variables and more demanding fixed effects.

Insert Table 4, 5, 6, and 7 here

4 Impact after the strike

As established in the previous section, it is primarily the closeness of substitution which increased demand *during* the rail strike. In this section, I test for any persistence of the effect *after* the rail strikes. Treatment and control groups are defined using the channel identified in the first step, namely the *bus travel time* proxy variable. As previously done, I code the treatment variable as a dummy equal one if the bus travel time of the route is below the median bus travel time.[23]

The post-strike regression takes the following form:

$$\begin{aligned}\ln \text{ticket sales}_{ijt} \; &= \alpha_{ij} \; + \; \tau_t \; + \; X_{it} \; + \; X_{jt} \\ &\quad + \; \delta_1 \; (\text{treated}_{ij} \times \text{strike}_t) \; + \; \delta_2 \; (\text{treated}_{ij} \times \text{post}_t) \; + \; \epsilon_{ijt}\end{aligned} \tag{2}$$

Equation 2 is very similar to Equation 1 in Section 3. I employ the same combination of specifications, control variables and fixed effects. The difference-in-differences (DD) methodology compares changes in the ticket sales of MFB between routes that differed in their closeness of substitution as measured by the absolute bus travel time.

However, the underlying data now also includes the post-strike period. I am interested in whether routes that were 'more treated' had significantly more customers beyond the strikes compared to the 'less treated' routes. Furthermore, the dependent variable *ln ticket sales*$_{ijt}$ is defined as the log total number of MFB customers. I no longer restrict it to new customers who booked during the final three days to departure, because I would like to investigate whether customers adjust their modal choice after their first experience of buses during the strike. The dependent variable now includes returning customers, some of whom travelled by bus for the first-time during the strike.

treated$_{ij}$ indicates if a route was part of the treatment group, i.e. whether the bus travel time is shorter than the median. The interaction term ($\textit{treated}_{ij} \times \textit{strike}_t$) captures the effect during the strikes and should yield positive and statistically significant coefficients because this is how treatment was selected. The coefficient of ($\textit{treated}_{ij} \times \textit{post}_t$) then captures the treatment effect of interest: whether the treated group has significantly higher ticket sales *after* the rail strikes, that is after DB services returned back to normal operations.

Insert Table 8 here

Table 8 reports regression results for Equation 2. The table indicates that there was a statistically positive and significant effect beyond the duration of the rail strike. While the effect is significantly smaller in magnitude than the effect of treatment during the rail strike, it is remarkably persistent.

[23]See the robustness section for a continuous definition of the treatment variable.

Column 1 of Table 8 suggests that total ticket sales for the treated routes were almost 15 percent higher in the first strike wave, 30 percent higher in the second strike wave, and 40 percent higher in the third strike wave. Ticket sales were about 25 percent higher for the treated group after rail operations returned back to normal. Its magnitude is roughly the same once I include controls and different sets of fixed effects, and robust to a number of alternative specifications provided in the robustness section.

However, whether the effect can be interpreted causally depends on the identification assumption: would ticket sales for routes in the treatment group have changed the same during and after the railway strikes in the absence of a strike. I address this assumption below and present a number of robustness checks.

4.1 The common trend assumption

This chapter shares the typical advantages and disadvantages of a standard DD strategy. On the one hand, DD allows me to control for all time-invariant differences across routes as well as changes over time by including both route and time-period fixed effects. On the other hand, the DD identification hinges on the strong but easily stated assumption of a common trend: would treatment and control groups move in parallel in the absence of treatment? There may be time-varying confounding factors that are correlated with the treatment group.

To address whether the common trend assumption holds in this setting, I discuss a number of tests. Firstly, I use strong sets of fixed effects. My specification includes a number of time- and route-varying controls, as well as origin- and destination-specific linear trends. The different fixed effects capture any level effects such as distance or common seasonal variations. They also capture time-varying omitted variables such as MFB marketing expenditures. The origin- and destination-day fixed effects also capture possible linear trends. In addition, I estimate a specification with route-specific trends in Section 5.1 below. What remains are time-varying confounding factors that are correlated with the treatment groups.

Secondly, Figure 8 graphically compares the trend between the treatment and control groups for the mean log number of ticket sales to all and first-time customers. The common trend assumption meets the eyeball test. Before the rail strike, treatment and control group move remarkably in parallel. As expected, the treated group displays a visibly larger increase in sales during the strikes. The figure reports weekly averages, but a graph of daily ticket sales split by weekday yields the same result.

Insert Figure 8 here

Thirdly, I re-estimate Equation 2 with pre-strike and post-strike treatment effects.[24] I report weekly coefficients to remove any weekday cyclicality. The estimated treatment effects for the pre-strike period act as a test for the common trend assumption. The pre-strike coefficients can be thought of as placebos. If trends are the same, the pre-strike coefficients should be constant and small in magnitude. If, however, pre-trends are present they would show up in the treatment group.

The specification takes the following form:

$$\begin{aligned} \ln \text{ticket sales}_{ijt} &= \alpha_{ij} + \tau_t + X_{it} + X_{jt} \\ &\quad + \delta_t \, (\text{treated}_{ij} \times \text{week}_t) + \epsilon_{ijt} \end{aligned} \tag{3}$$

where $week_t$ is a vector of week-fixed effects. The coefficients of interest, that is vector δ_t, must be measured relative to a baseline period. I normalize with respect to the first week of the sample which is standard in the literature. As above I run an additional specification with origin- and destination-departure day fixed effects. Unlike the previous specifications Equation 3 includes observations for the two days before and after each strike as well as the intermediate period between the second and third strike wave.

The plot of coefficients is reported in the main results section as Figure 9.[25] The coefficients report the correlation between the treated group (short bus routes) and the outcome of interest (log ticket sales) for each period. This has the additional advantage that I can evaluate the effect of the strikes over the course of the post-period: the week coefficients allow me to evaluate the effect at different elements of the post-period, as opposed to estimating an average effect only. It may take some time for the full effect to show up or for it to die out over time. The estimated weekly treatment coefficients are flexible in assessing the short- and medium-term effects.

[24] Nunn and Qian (2011) and Autor (2003) provide good examples of estimating period-specific treatment effects in a difference-in-differences setting.

[25] Tables reporting coefficients of control variables and the exact coefficients are omitted for length but available upon request.

The weekly treatment coefficients are reported in Figure 9. They display a remarkably persistent effect of the rail strike. There is a jump in the magnitude of the estimated treatment coefficients at the time of rail strikes. This jump in the magnitude of the estimated coefficients persists beyond the rail strikes until the end of the sample period. The post-strike treatment coefficients are constant around 0.4. Thus ticket sales to the treatment group are 40% higher than in the baseline period. The pattern of period-specific treatment coefficients is analogous to that of Nunn and Qian (2011). They also estimate period-specific treatment effects, and find coefficients that are constant and small in in the pre-period and increase in magnitude after treatment.

Insert Figure 9 here

While there is a clear jump in the magnitude of the coefficients around the time of the strike, two issues cast doubt on the parallel trends assumption. Firstly, the magnitude of the treatment coefficients starts increasing too early, i.e. a week before the first two strike waves. This suggests that ticket sales for short routes already grew more strongly before the rail strike. Secondly, the post-strike coefficients are larger than the treatment coefficients during the strike, which is worrisome. This suggests that the common trend assumption is not completely tenable in the given context. If these different trends would simply reflect the heterogeneous effect of seasonality on short and long routes, and I had data from 2013, this problem may be addressed using a triple-difference-in-differences approach. However, even if these data were available the large changes in the inter-city bus market may not allow for an appropriate removal of seasonal effects.

5 Robustness

5.1 Route specific trends

Based on these results, this subsection estimates possible remedies. The possible violation of the common trend assumption suggests that there are factors which cause ticket sales to evolve differently on the control and treatment routes. For instance, there might be route-specific trends related to characteristics that affect ticket sales. I estimate two additional specifications with route-specific trends, $(\alpha_{ij} \times t)$. These capture any potential linear trend specific to each route. The regression takes the following form:

$$\begin{aligned} \ln \text{ticket sales}_{ijt} \; &= \alpha_{ij} \; + \; \tau_t \; + \; \gamma_{it} \; + \; \gamma_{jt} \; + \; X_{it} \; + \; X_{jt} \; + \; (\alpha_{ij} \times t) \\ &+ \; \delta_t \; (\text{treated}_{ij} \times \text{week}_t) \; + \; \epsilon_{ijt} \end{aligned} \tag{4}$$

The estimated coefficients of the $(\text{treated}_{ij} \times \text{week}_t)$ interaction term in Equation 4 are plotted in Panels 1 and 2 of Figure 10. Because I cannot include route-clustered standard errors due to insufficient observations, I report robust standard errors. With this specification, the effect of the strikes will only be captured if there is a stark deviation from the trend (Angrist and Pischke, 2014). In this case, the common trend assumption does not appear to be violated.

A second specification with route-specific trends repeats the estimation using pre-period observations only following Repetto (2016): I estimate ϕ_{1ij} and ϕ_{2ij} using only data from the pre-strike period (September 01-October 14) in a quadratic trend model:

$$\ln \text{ticket sales}_{ijt} \; = \; \phi_{1ij}t \; + \; \phi_{2ij}t^2 \; + \; u_{ijt} \tag{5}$$

I then add the estimates for ϕ_{1ij} and ϕ_{2ij}, that is $\widehat{\phi_{1ij}}$ and $\widehat{\phi_{2ij}}$, back into the main specification. This method 'projects' pre-strike trends into the post-strike period:

$$\begin{aligned} \ln \text{ticket sales}_{ijt} \; &= \alpha_{ij} \; + \; \tau_t \; + \; \gamma_{it} \; + \; \gamma_{jt} \; + \; X_{it} \; + \; X_{jt} \\ &+ \; \delta_{\phi_1} \; (\widehat{\phi_{1ij}} \times t) \; + \; \delta_{\phi_2} \; (\widehat{\phi_{2ij}} \times t^2) \\ &+ \; \delta_t \; (\text{treated}_{ij} \times \text{week}_t) \; + \; \epsilon_{ijt} \end{aligned} \tag{6}$$

This specification controls for route-specific trends that were in place before the strikes and that may cause ticket sales patterns to be different across groups. I report results in Panels 3 and 4 of Figure 10. As above, I report results for both variables in the same figure, and only report coefficients for regressions including the complete set of control variables.

Insert Figure 10 here

On the one hand, Panels 1 and 2 of Figure 10 report the specification with route-specific trends. I no longer find any statistically significant effect. However, this result may simply be due to the inability to include clustered standard errors into this specification. The route-specific pre-trends, on the other hand, confirm the earlier result. Although the common trend assumption does not appear to be completely tenable in the given context, the lasting and remarkably persistent post-treatment effects for the treated routes is still visible.

5.2 Other robustness

In this subsection, I consider a host of additional factors, alternative specifications, and different definitions of the dataset to verify my previous results. For length, all regression tables are reported in Appendix 6.3.

First, I conduct a robustness check with treatment defined as a continuous variable. A continuous 'treatment' is harder to interpret, but captures more variation in the channel variable. The regression results with the explanatory variable specified as the natural logarithm of bus travel time yield statistically significant coefficients equivalent to my previous results. In addition, I confirm that using variable *absolute travel time difference* for the post-strike regressions yields equivalent results.

Second, GDL membership rates are higher in East Germany because many train drivers in West Germany are civil servants. Travellers may not have been aware of the precise emergency timetables, and simply considered the effect of GDL strikes to be starker in East Germany. In that case, the relevant transmission channel would be to split routes into West- and East- Germany. Note that this specification does not allow for the inclusion of origin-day and destination-day fixed effects. I do not find that using this distinction explains MFB ticket sales during the strikes.

Third, I re-run my estimation with Berlin omitted from the sample. Berlin is special because inter-city buses were liberalized before 2013 – a historical relic from the Cold War division of Germany. My results are unaltered if I drop all routes to and from Berlin.

Fourth, I re-run my estimation of the effect *during* the strikes using ticket sales to all consumers as the dependent variable. While the estimated coefficients are lower, this change does not alter the previous results in a meaningful way. Bus travel time is the only factor that significantly explains MFB ticket sales during the strike. The same holds true if I do not drop the two days before and after each rail strike and include the intermediary week between the second and third strike wave.

Fifth, long routes are more likely to be served by aeroplanes. Customers may have switched to buses on routes with a short bus travel time because aircraft do not serve these routes. In this case, the short bus travel time would not be a proxy for closeness of substitution, but lack of other alternatives to rail. To address this concern, I show that my main results is insensitive to a re-run of my estimation where I restrict the sample to routes with no substantial national flight service.[26] During the sample period Germany's largest airline *Lufthansa* was also affected by strikes due to a labour dispute with its pilots. While an airline strike would primarily affect long bus routes, this robustness check also addresses spillover concerns from *Lufthansa* strikes.

Insert Figure 11 here

Sixth, a concern might be the presence of unobserved marketing activity by MFB. A marketing campaign may have coincided with the rail strikes and targeted routes with a short bus travel time. While I do not have data on MFB's marketing budget, my dataset includes information on whether MFB sold a ticket at a discount. For example, MFB may have handed out vouchers or offered discounts via its mobile phone Application. Using discounts as a proxy for MFB marketing activity, Figure 11 plots the mean fraction of tickets that received a discount for each departure day split by treatment and control group. The fraction of tickets that receive a discount fluctuates between 2 and 4 percent in the sample period. Based on this proxy measure, there is neither evidence that MFB increased its marketing activity in general, nor for the treatment group.

Seventh, an additional concern might be that travellers booked bus tickets after the November 2014 rail strike, because they were worried about potential future strikes. The rail strikes lasted beyond the strikes in 2014, and the labour dispute was only resolved after additional strike waves in April and May 2015. However, immediately after the strike wave in November GDL announced a temporary truce. It would refrain from industrial action until the new year. Even though some customers may have distrusted the truce, it is unlikely that increased bus ticket sales in this period are driven by the fear of new strikes.

Eighth, a further concern might be that many travellers are locked in to DB because they hold season passes. While DB does not offer season passes, it operates the *BahnCard* – a frequent traveller card

[26]To be precise, I drop the largest 10 bi-directional connections (20 routes) within Germany. This covers all city connections with an excess of 0.4 million annual passengers in 2016. Source: ADV Airport association

granting fixed price reductions. More than half of all DB ticket sales receive discounts through the *BahnCard*.[27] Travellers may have waited for their *BahnCard* to expire before they switched to inter-city buses. While it is possible that any effects may not show up until later, my period-specific treatment effects suggest an immediate impact.

Finally, my dataset permits me to observe return ticket bookings. I confirm that my results are not sensitive to the inclusion of return tickets bought in a single booking session.

6 Conclusion

This chapter exploits a novel and extremely rich dataset to investigate the effects of the 2014-2015 German railway strikes – the largest in German history – on the domestic demand for inter-city buses. The railway strikes provide a quasi-natural experiment setting to analyse the general question of whether a temporary shock can have lasting effects on one's competitors' demand.

I first test a number of potential transmission channels for inter-city bus demand, since it is not ex-ante clear which bus routes were affected *during* the rail strike. The results show that the only channel predicting peak ticket sales for MeinFernbus during the rail strikes is the closeness of substitution to the rail. Customers switched to inter-city buses if the absolute travel time difference was small or the absolute bus travel time was short. There is no evidence that travellers took into account the regional variation of the exposure to the rail strike, as measured by the fraction of cancellations and expected delay, in their decision on whether to switch to buses or not. Either they were not well informed about their exposure to the strikes as specified in the emergency timetables published by DB, or they may simply not have trusted DB's ability to implement the emergency timetables. In a second step, I use the channel identified in the first step, to test whether the strikes brought about lasting changes *after* DB services returned to normal operations. Although the common trend assumption does not seem to be completely tenable in the given context, my results still suggest a lasting effect on the ticket sales for inter-city buses on the affected routes. This result is robust to a number of alternative specifications, such as the inclusion of route-specific pre-trends.

[27] Source: Welt.de (url: *https://www.welt.de/wirtschaft/article1069965/Die-Bahncard-hat-Verspaetung.html*; 31/07/2007)

The findings of this chapter open questions for future research. Given the history of interaction between GDL and DB, future rail strikes are very likely. Since the inter-city market for buses has consolidated substantially since 2014, future research may be able to remove seasonal effects and establish a stronger causal effect for the persistence of rail strikes on bus demand. Another intriguing avenue would be to uncover the potential mechanisms at play. These may range from new information asymmetries to retaliatory motives.

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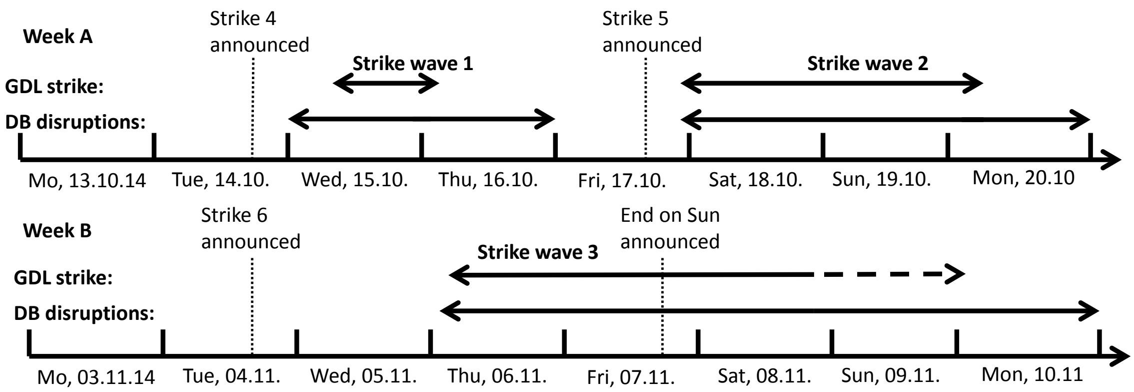
Table 1
Dates and duration of railway strike waves in 2014-2015

Nr.	Strike Begin:	—	Strike End:	Duration (in hours):
1	Mon. 01/09/2014, 18:00	—	Mon. 01/09/2014, 21:00	3*
2	Sat. 06/09/2014, 06:00	—	Sat. 06/09/2014, 09:00	3*
3	Tue. 07.10.2014, 21:00	—	Wed. 08.10.2014, 06:00	9*
4	**Wed. 15/10/2014, 14:00**	**—**	**Thu. 16/10/2014, 04:00**	**14**
5	**Sat. 18/10/2014, 02:00**	**—**	**Mon. 20/10/2014, 04:00**	**50**
6	**Thu. 06/11/2014, 02:00**	**—**	**Sat. 08/11/2014, 18:00**	**64**
7	Wed. 22/04/2015, 02:00	—	Thu. 23/07/2015, 21:00	43
8	Tue. 05/05/2015, 02:00	—	Sun. 10/05/2015, 09:00	127
9	Wed. 20./05/2015, 02:00	—	Thu. 21./05/2015, 19:00	41

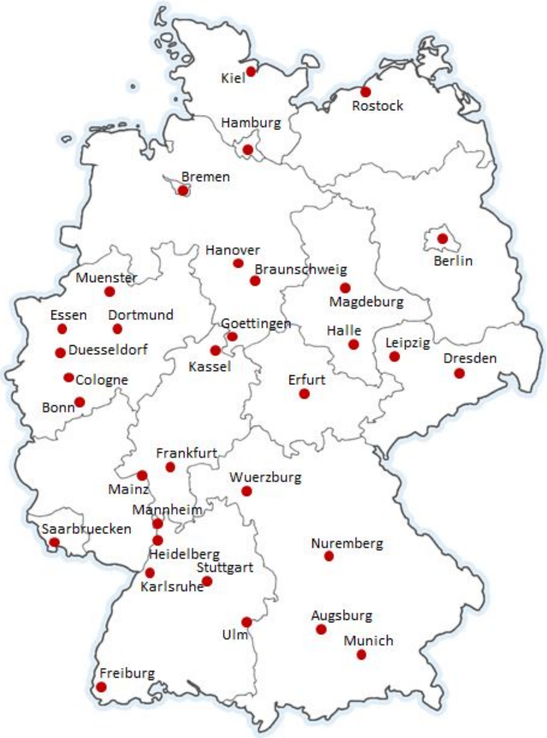
Notes: Bold rows indicate waves studied in this chapter. Strikes in 2015 are disregarded, because they coincide with the merger of MFB and rival competitor Flixbus in January 2015. * indicates warning strikes. Warning strikes are ignored, because they only lasted a few hours and were announced with many days' advance warning.

Figure 1
Timeline of rail strike in weeks October 13-20 and November 03-10, 2014



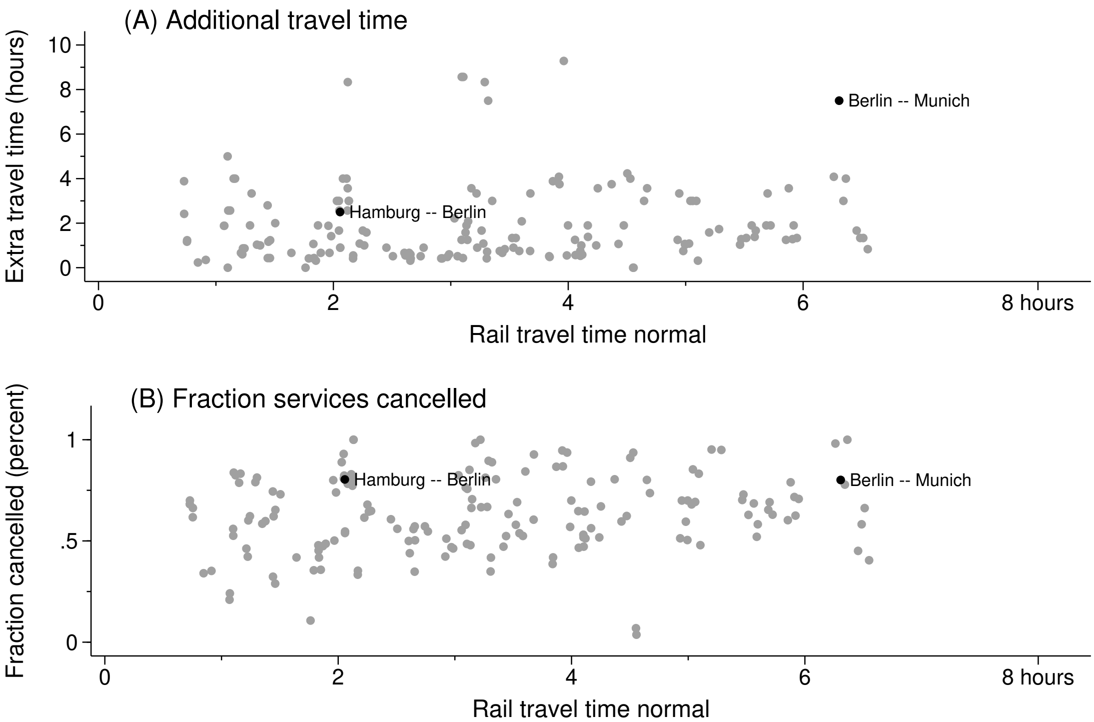
Notes: DB disruptions start before the first strike wave because DB adopted its emergency timetables with the beginning of the departure day to minimize the overall impact of the strike. DB disruptions lasted beyond the duration of each strike wave as it took time to return to normal timetable operations. Furthermore, the third rail strike wave in week B was ended prematurely on Saturday, although it had initially been announced to last until Sunday (as indicated by the dashed line). Following public pressure, the GDL announced it would return to work on Sunday November 9^{th} to allow travellers to reach the anniversary festivities of the Fall of the Berlin Wall around the country. Strikes 4-6 refer to Table 1. Throughout this paper I refer to the strikes as waves 1-3.

Figure 2
Map and list of German cities in the sample



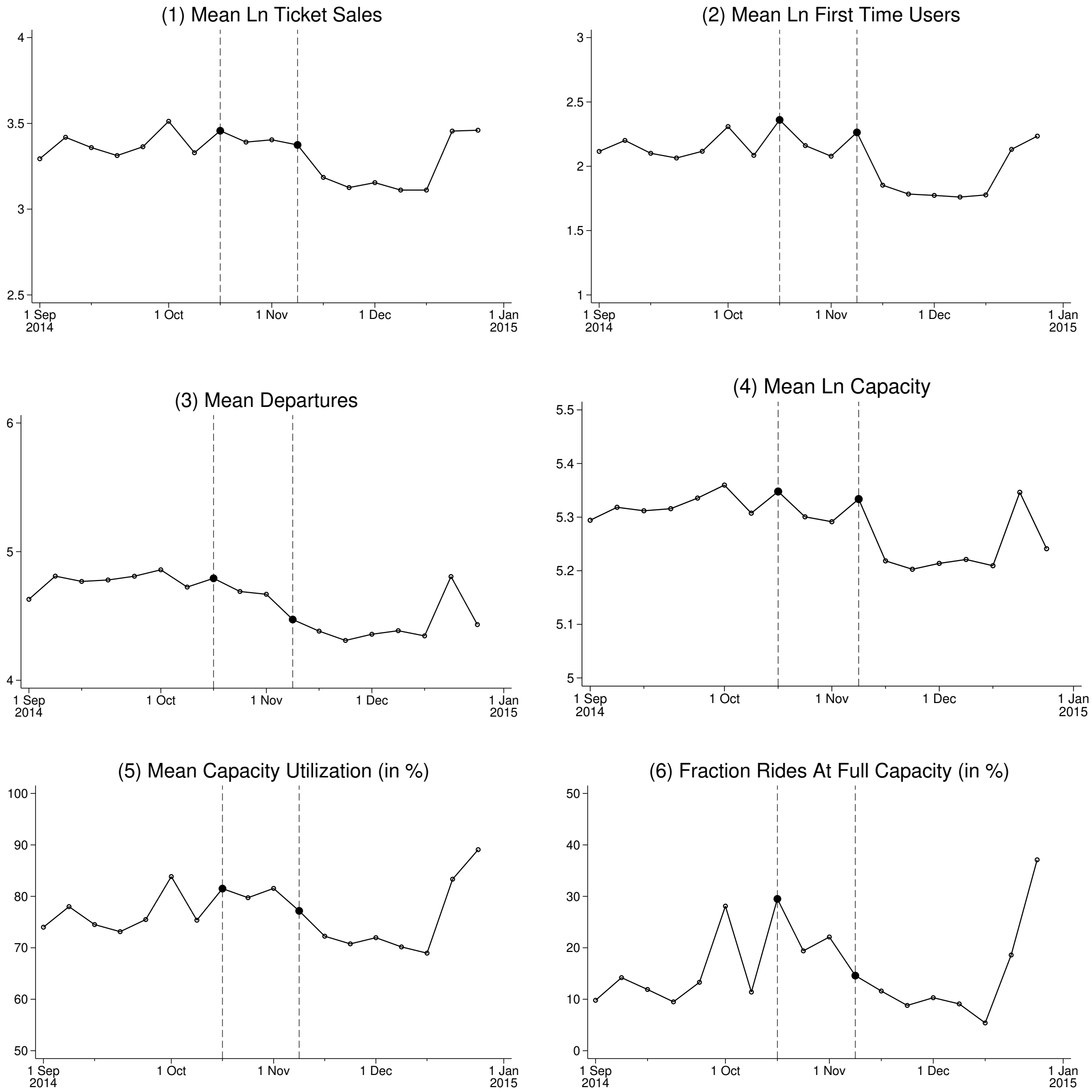
Cities:	
Augsburg	Heidelberg
Berlin	Karlsruhe
Bonn	Kassel
Braunschweig	Kiel
Bremen	Leipzig
Cologne	Mainz
Dortmund	Magdeburg
Dresden	Mannheim
Duesseldorf	Munich
Erfurt	Muenster
Essen	Nuremberg
Frankfurt (Main)	Rostock
Freiburg	Saarbruecken
Goettingen	Stuttgart
Hamburg	Ulm
Halle (Saale)	Wuerzburg
Hanover	

Figure 3
Panel A: DB travel time normal vs. expected additional travel time.
Panel B: DB travel time normal vs. and fraction of services cancelled for each route during the rail strike



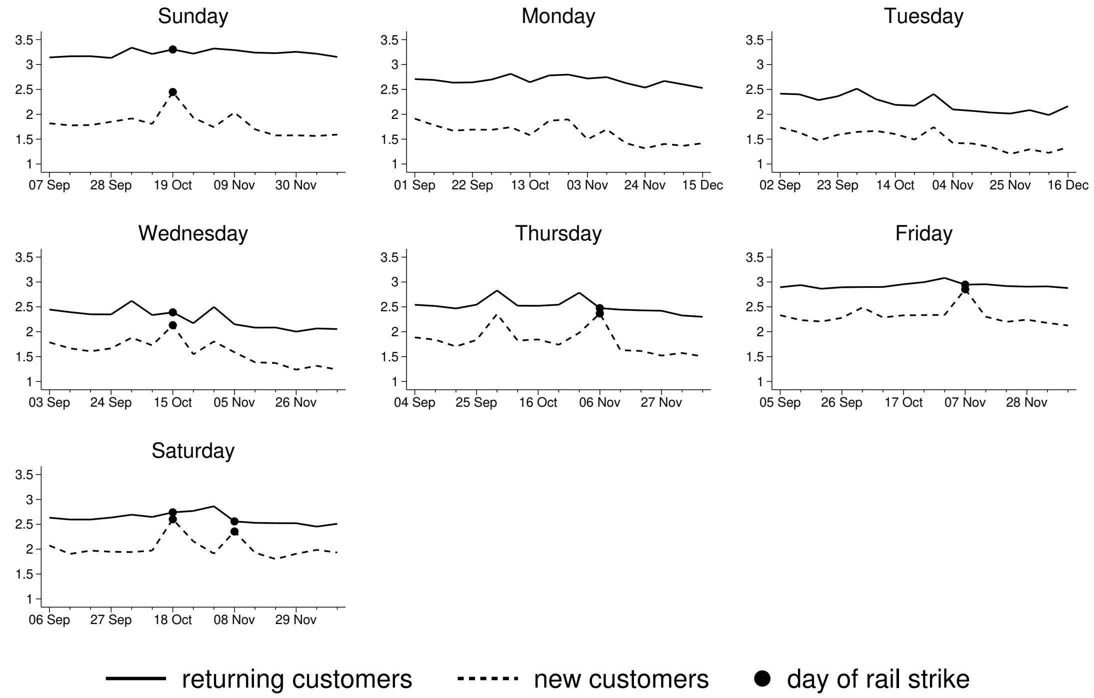
Notes: Datasource DB emergency timetables. Routes Munich–Berlin and Hamburg–Berlin are highlighted as examples.

Figure 4
Aggregate weekly descriptives on MFB ticket sales and supply



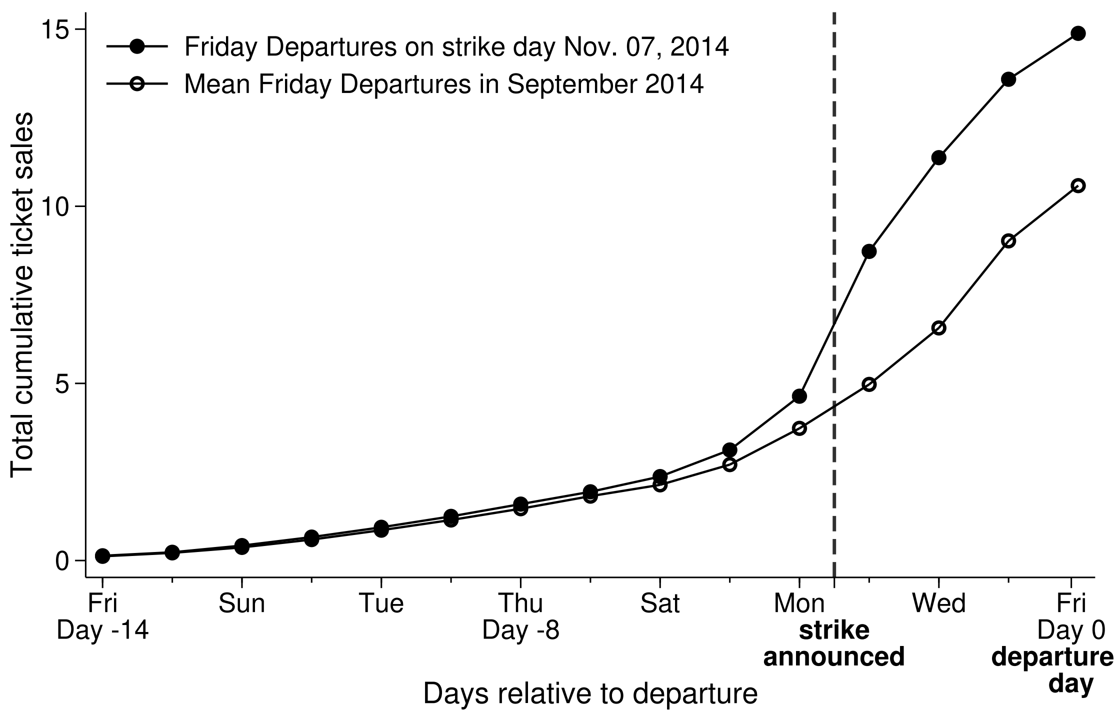
Notes: Sample at route - departure date dimension. Panels 1-4 report weekly averages over all routes. Panels 5 and 6 report averages for each bus journey. Panel 1 reports the average log number of total tickets. Panel 2 reports the log number of total tickets sold to first-time customers. Panel 3 reports the average daily departures per route. Panel 4 the daily capacity per route. Panels 5 and 6 report descriptives relating to the capacity utilization of MFB services. Vertical line and bold circles indicate weeks in which GDL was on strike.

Figure 5
Mean total ticket sales split by returning and new customers



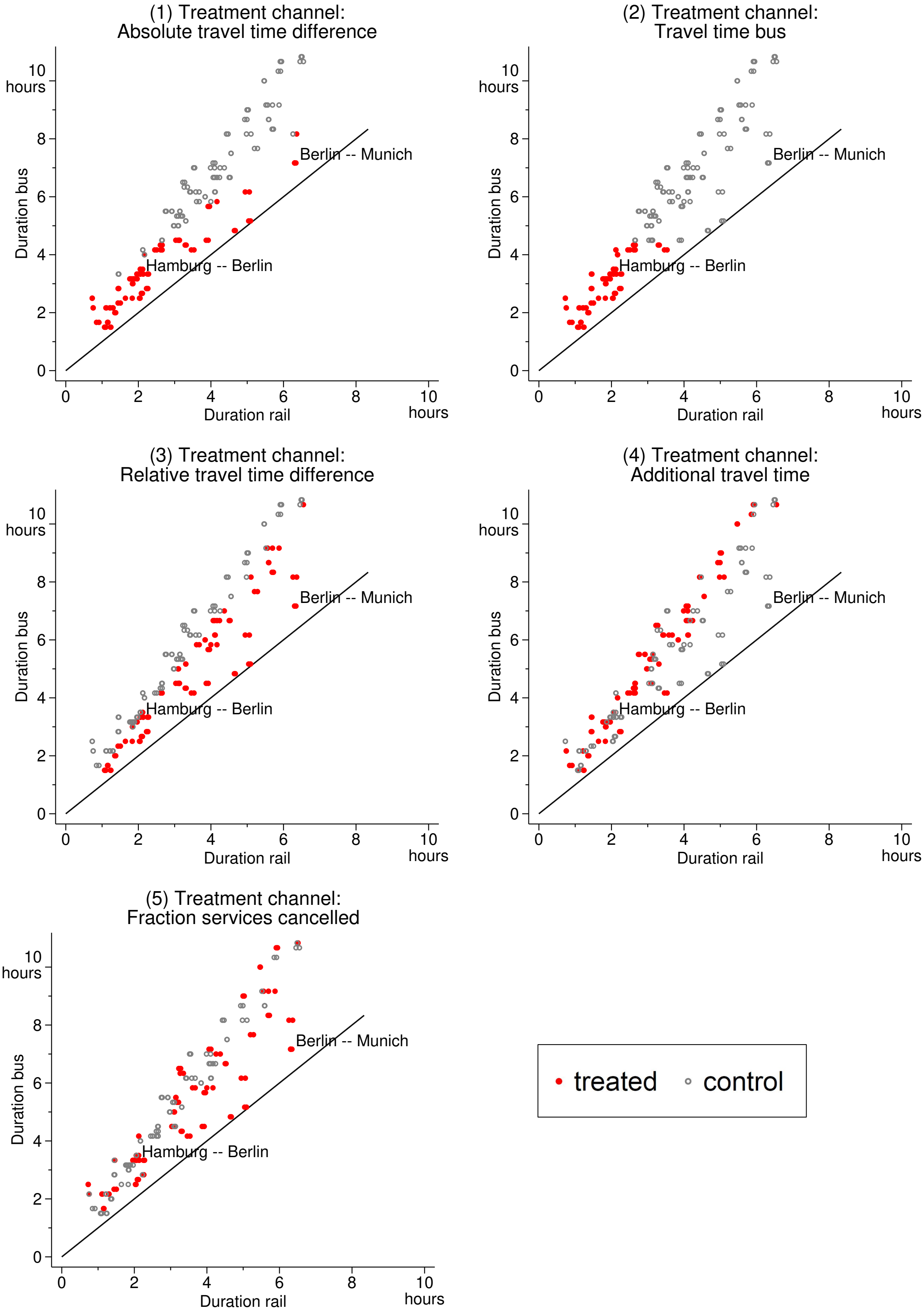
Notes: Data are split by weekday and bold circles indicate that the weekday was affected by a strike.

Figure 6
Mean cumulative bookings for Friday departures



Notes: Data are split into bookings for Friday-departures in September, the month just preceding the rail strike, and bookings for departures for strike day November 07, 2014. The strike was announced 3 days prior to the strike (as indicated by the dashed line). Note that ticket sales are not in log scale here.

Figure 7
Treated and control routes for each channel variable



Notes: Each panels display scatter of routes in duration rail and duration bus space with 45 degree line. For each proxy transmission variable, Panels 1-5 indicates whether a route is part of the treatment or control group. *Relative travel time*, *absolute travel time* and *bus travel time* are treated if the route is shorter than the median. *Fraction services cancelled* and *additional travel time* are treated if the route is above the median value. See Table 9 for specific variable definitions). Routes Hamburg–Munich and Munich–Berlin plotted as examples.

Table 2
Summary statistics for whole sample period

Variable:	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**
Dependent variables:						
ln ticket sales$_{ijt}$	33,384	2.50	2.40	1.12	0	6
ln ticket sales$_{ijt}^{\text{new}}$	33,384	1.35	1.39	1.01	0	6
Proxy channel variables (channel$_{ij}$):						
Fraction services cancelled	17,762	0.63	0.63	0.19	0	1
Additional travel time	17,762	114.67	78.50	106.36	0	557
Relative travel time	17,762	1.64	1.64	0.34	1	4
Abs. travel time difference	17,762	116.99	109.89	67.53	5	285
Bus travel time	33,384	289.10	265.00	149.29	60	650
Control variables (X_{it} and X_{jt}):						
School holiday	33,384	0.30	0.00	0.46	0	1
Public holiday	33,384	0.04	0.00	0.20	0	1
Bundesliga (Division 1)	33,384	0.00	0.00	0.05	0	1
Bundesliga (Division 2)	33,384	0.00	0.00	0.02	0	1
Munich Oktoberfest	33,384	0.02	0.00	0.14	0	1
Stuttgart Wasen	33,384	0.02	0.00	0.14	0	1

Notes: Variables fraction services cancelled, additional travel time, relative travel time and absolute travel time difference have fewer observations because emergency time tables do not include information on regional trains. In addition, Table 9 in Appendix 6.1 provides definitions of all variables estimated in Equations 1 to 6.

Table 3
Summary of regression results

Nr.	Table Nr.	Transmission channel:		Strike wave: 1	2	3
		1. Closeness of substitution:				
1	4	Bus travel time		✓	✓	✓
2	5	Absolute travel time difference		✓	✓	✓
3	10	Relative travel time difference		✗	✗	✗
		2. Exposure to rail strike:				
4	11	Additional travel time		✗	✗	✗
5	12	Fraction services cancelled		✗	✗	✗
		3. Combination of 1. and 2. (triple interactions):				
		Channel 1:	*Channel 2:*			
6	13	Bus travel time	Additional travel time	✗	✗	✗
7	14	Bus travel time	Fraction services cancelled	✗	✗	✗
8	15	Absolute travel time	Additional travel time	✗	✗	✗
9	16	Absolute travel time	Fraction services cancelled	✗	✗	✗
10	17	Relative travel time	Additional travel time	✗	✗	✗
11	18	Relative travel time	Fraction services cancelled	✗	✗	✗

Notes: Summary of regression results from Equation 1. Regression figures are reported in Appendix 6.2. ✓ indicates positive and statistically significant coefficients at the 1% level for all combinations of fixed effects and controls reported in the regression table. ✗ otherwise. Please refer to Table 9 for variable definitions.

Table 4
Transmission channel: bus travel time

	Dep. variable: ln ticket sales$_{ijt}^{new}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Channel × Strike wave 1	0.257***	0.265***	0.249***	0.262***
	(0.0614)	(0.0613)	(0.0603)	(0.0673)
Channel × Strike wave 2	0.408***	0.389***	0.369***	0.302***
	(0.0516)	(0.0513)	(0.0512)	(0.0633)
Channel × Strike wave 3	0.488***	0.451***	0.426***	0.395***
	(0.0459)	(0.0456)	(0.0440)	(0.0514)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.748	0.754	0.757	0.816
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level. 166 clusters. ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day t specific fixed effects.

Table 5
Transmission channel: absolute travel time difference

	Dep. variable: ln ticket sales$^{new}_{ijt}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Channel × Strike wave 1	0.154** (0.0605)	0.170*** (0.0593)	0.172*** (0.0578)	0.148** (0.0720)
Channel × Strike wave 2	0.218*** (0.0597)	0.218*** (0.0582)	0.220*** (0.0560)	0.234*** (0.0667)
Channel × Strike wave 3	0.226*** (0.0521)	0.188*** (0.0559)	0.222*** (0.0512)	0.308*** (0.0607)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.744	0.751	0.755	0.815
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level. 166 clusters. ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day t specific fixed effects.

Table 6
Transmission channel: Absolute travel time difference vs. bus travel time

		Dep. variable: ln ticket sales$^{new}_{ijt}$			
		(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Absolute difference	× Strike wave 1	-0.0219 (0.0793)	-0.0379 (0.0758)	-0.0460 (0.0756)	-0.166* (0.0886)
Absolute difference	× Strike wave 2	-0.0926 (0.0665)	-0.0920 (0.0659)	-0.101 (0.0671)	-0.200*** (0.0765)
Absolute difference	× Strike wave 3	-0.0740 (0.0634)	-0.0858 (0.0613)	-0.0954 (0.0608)	-0.103 (0.0650)
Duration bus	× Strike wave 1	0.247*** (0.0677)	0.248*** (0.0664)	0.228*** (0.0665)	0.189** (0.0755)
Duration bus	× Strike wave 2	0.365*** (0.0570)	0.346*** (0.0571)	0.323*** (0.0568)	0.215*** (0.0687)
Duration bus	× Strike wave 3	0.453*** (0.0485)	0.411*** (0.0487)	0.382*** (0.0505)	0.351*** (0.0573)
Add. Controls			✓	✓	
Origin - trend				✓	
Destination - trend				✓	
Day FEs		✓	✓	✓	
Route FEs		✓	✓	✓	✓
Origin-Day FEs					✓
Destination-Day FEs					✓
Observations		15600	15600	15600	15400
R^2		0.748	0.754	0.757	0.816
Clustered SEs		✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level. 166 clusters. ***/**/* indicate significance at the 1%/5%/10% level. γ_{it} and γ_{jt} refer to specifications with origin- and destination-day t specific fixed effects.

Table 7
Transmission channel: Transmission channel: 3 hour bins for bus travel time

		Dep. variable: ln ticket sales$_{ijt}^{new}$			
		(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Strike wave 1	× Duration 6 - 9 hours	0.0936 (0.133)	0.135 (0.130)	0.101 (0.126)	0.108 (0.143)
Strike wave 1	× Duration 3 - 6 hours	0.289** (0.126)	0.310** (0.125)	0.280** (0.120)	0.324** (0.143)
Strike wave 1	× Duration 0 - 3 hours	0.411*** (0.129)	0.472*** (0.131)	0.435*** (0.125)	0.472*** (0.154)
Strike wave 2	× Duration 6 - 9 hours	0.408*** (0.119)	0.405*** (0.115)	0.366*** (0.123)	0.345** (0.142)
Strike wave 2	× Duration 3 - 6 hours	0.556*** (0.117)	0.543*** (0.113)	0.508*** (0.120)	0.495*** (0.146)
Strike wave 2	× Duration 0 - 3 hours	0.942*** (0.119)	0.920*** (0.116)	0.878*** (0.122)	0.800*** (0.157)
Strike wave 3	× Duration 6 - 9 hours	0.411*** (0.131)	0.378*** (0.126)	0.326*** (0.122)	0.351*** (0.124)
Strike wave 3	× Duration 3 - 6 hours	0.702*** (0.129)	0.642*** (0.124)	0.606*** (0.120)	0.630*** (0.123)
Strike wave 3	× Duration 0 - 3 hours	0.980*** (0.131)	0.911*** (0.126)	0.861*** (0.123)	0.869*** (0.131)
Add. Controls			✓	✓	
Origin - trend				✓	
Destination - trend				✓	
Day FEs		✓	✓	✓	
Route FEs		✓	✓	✓	✓
Origin-Day FEs					✓
Destination-Day FEs					✓
Observations		15500	15500	15500	15300
R^2		0.750	0.756	0.759	0.817
Clustered SEs		✓	✓	✓	✓

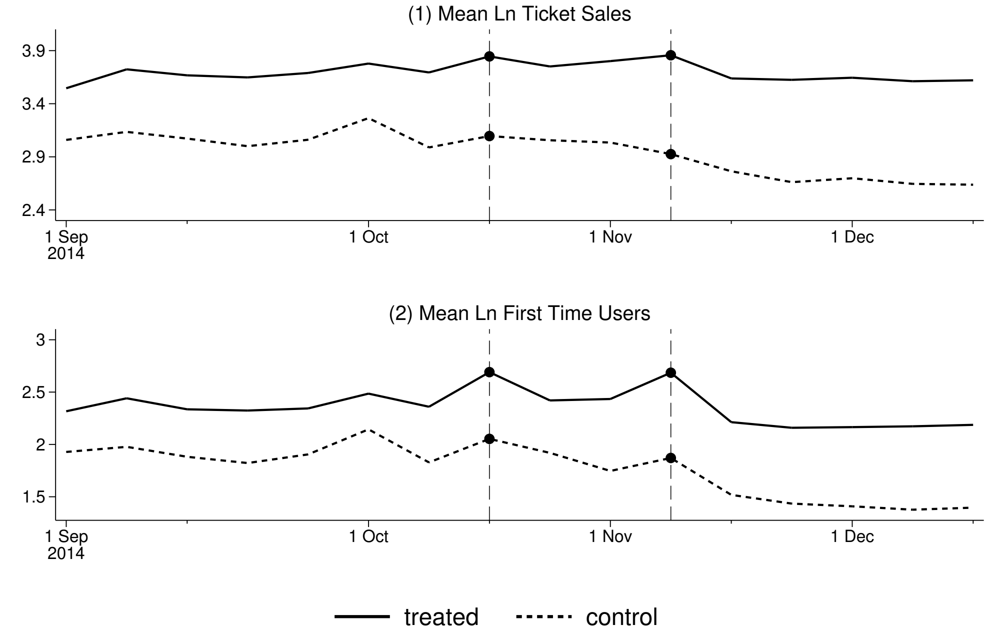
Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day t specific fixed effects.

Table 8
Impact after the strike – bus travel time

	Dep. variable: ln ticket sales			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Treated × Strike wave 1	0.131*** (0.0462)	0.136*** (0.0453)	0.137*** (0.0440)	0.127*** (0.0464)
Treated × Strike wave 2	0.291*** (0.0356)	0.273*** (0.0348)	0.273*** (0.0335)	0.230*** (0.0389)
Treated × Strike wave 3	0.387*** (0.0377)	0.359*** (0.0373)	0.356*** (0.0344)	0.322*** (0.0396)
Treated × Post	0.301*** (0.0228)	0.284*** (0.0221)	0.277*** (0.0196)	0.282*** (0.0224)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	26832	26832	26832	26488
R^2	0.875	0.878	0.881	0.912
Clustered SEs	✓	✓	✓	✓

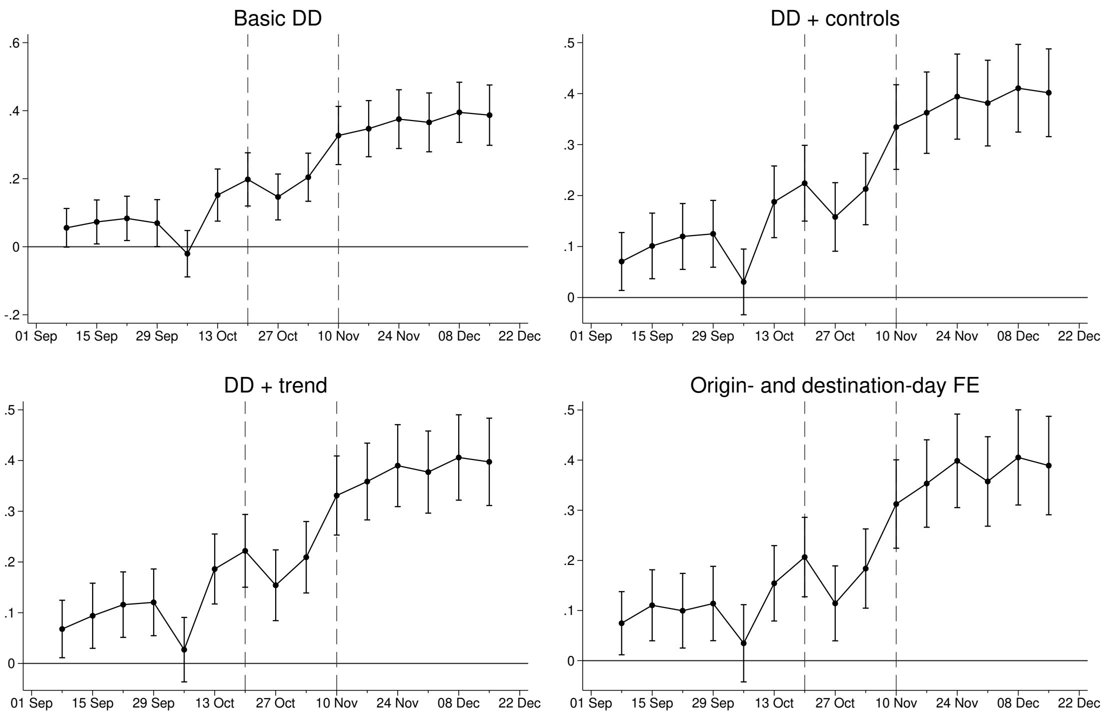
Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level. 166 clusters. ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day t specific fixed effects.

Figure 8
Mean log ticket sales split by treatment and control group



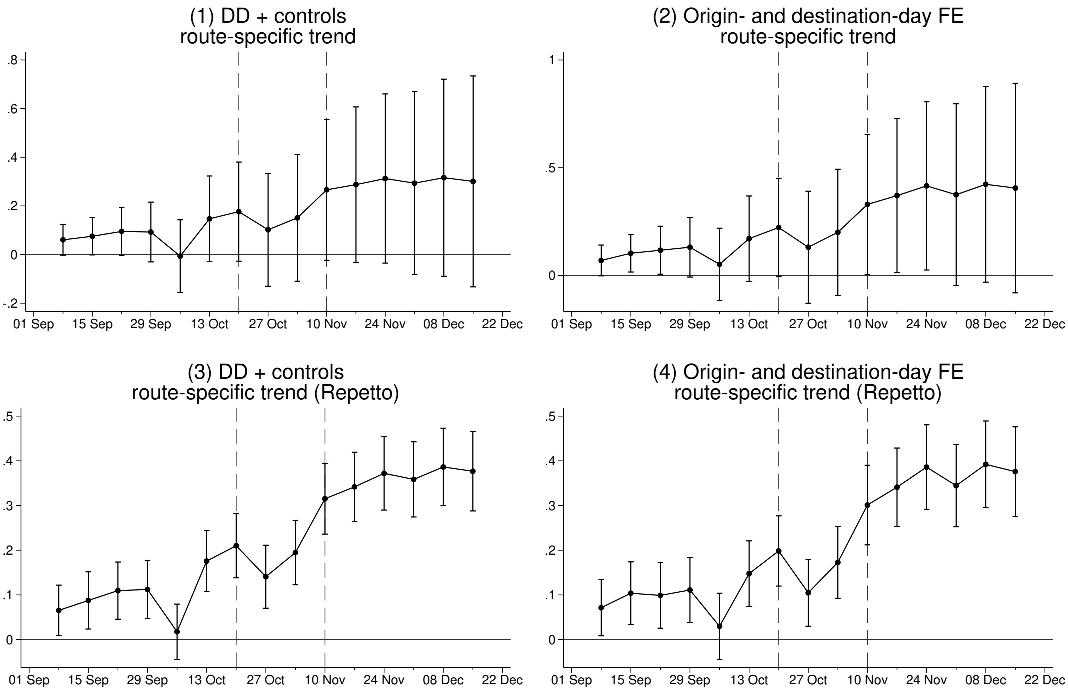
Notes: Sample period September 2014-January 2015. Vertical lines and bold circles indicate weeks and days, respectively, in which GDL was on strike.

Figure 9
Coefficients of the (treated$_{ij}$ × week$_t$) interaction term in Equation 3 with 95 percent confidence intervals.



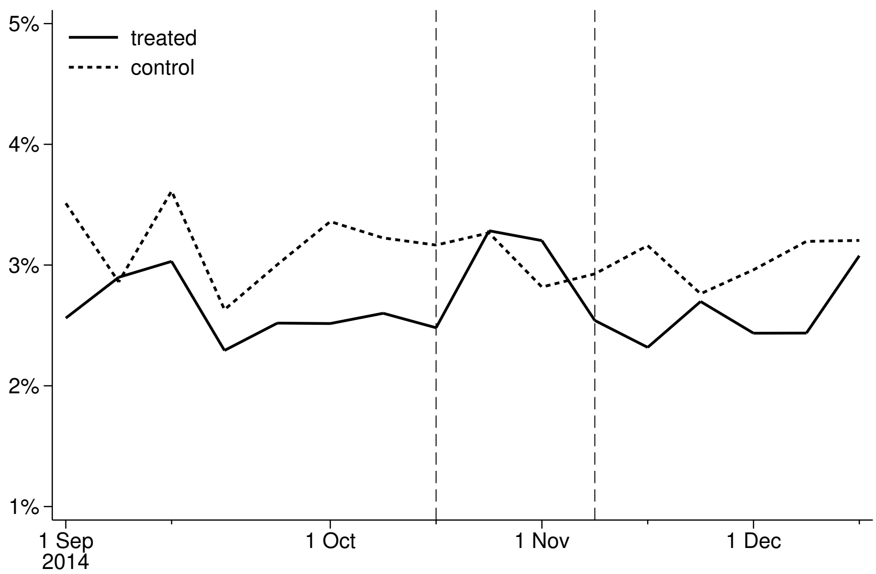
Notes: Dashed vertical line indicates weeks in which GDL was on strike. Standard errors clustered at the route level (166 clusters). Treatment variable: bus travel time.

Figure 10
Coefficients of the ($\text{treated}_{ij} \times \text{week}_t$) interaction term (route-specific trends)



Notes: Dashed vertical line indicates weeks in which GDL was on strike. Panels 1 and 2 report coefficients from Equation 4 (route-specific trends, robust standard errors.) with 95 percent confidence intervals. Panels 3 and 4 report coefficients from Equation 6 (route-specific trends following Repetto, 2016) with 95 percent confidence intervals. Panel 1-2: robust standard errors. Panel 3-4: route clustered standard errors. 166 clusters.

Figure 11
Mean fraction of tickets sold with a discount by treatment and control group



Notes: Vertical lines indicate weeks in which GDL was on strike.

Appendix

6.1 Data

MeinFernbus booking data

The route-day level bookings are constructed from an underlying dataset provided by MeinFernbus. It contains the universe of MFB bookings for all route combinations of 33 large German cities over the sample period for departure days from September 1^{st} to December 31^{st} 2014 – roughly 1.7 million observations. The dataset also includes individuals who departed in the sample period, but who booked their ticket outside the sample period.

The dataset provides detailed information on each booking such as the origin, destination, date and departure times of each service, as well as details on the individual booking process such as the time, date and whether a booking was via the web or an agency. The majority (>80%) of all bookings are made directly via the MeinFernbus website. For each booking via the internet an anonymized e-mail identifier is provided. Assuming for simplicity customer e-mails remain the same over time, this variable allows tracking individual booking behaviour over time. For agency bookings no data on individual e-mails is available. Furthermore, for each individual's e-mail the dataset records the first time a booking has been undertaken even if this was before the sample period. This allows classifying each bus customer into new and returning passengers. On the one hand, approximately 75 percent of bookings only appear once. On the other hand, about one percent of all individuals in the sample period travel regularly (more than seven times over the sample period).

In addition to the bookings, the dataset includes information on the supply of MeinFernbus services. The dataset identifies the total capacity of each bus, the line number and bus partner, as well as information on the prices charged. This allows identifying each individual journey (by bus id and route), and calculation of the total capacity of MeinFernbus buses for each departure day.

The set of routes includes all route combination of 33 large cities as depicted in Figure 2.[28] The cities and routes are spread across the entirety of Germany. Route selection was based on the most important cities in the bus network which approximately corresponds to the largest German cities. The choice of

[28]Note that I consider routes to be directional. For example, I treat Hamburg–Berlin and Berlin–Hamburg as two separate markets.

each city was justified based on the frequency of searches from a large online price comparison website. The data cover roughly 40 percent of the German inter-city bus market.[29] Exceptions are the exclusion of Bochum and Wuppertal as they are in the densely populated Ruhr-valley. To protect local public services, German law requires inter-city bus services to cover a minimum distance of 100km. Cities in the Ruhr-valley are frequently at a closer distance so no data on inter-city buses would be retrieved. I retain Ruhr-cities Dortmund and Essen. Furthermore, I include Freiburg because it is an important university town and Wuerzburg for its geographical centrality in Germany. Given the 33 cities in the sample there are 1056 possible routes spanning the simplex of these cities. 588 are served at least once. I focus on an even larger subset of routes: those routes that are served almost every day; i.e. not without at least one customer for more than 10 days in the sample.

A bus station is included if it is within 15 kilometre of the city centre. If there exist multiple bus stops within one city, my dataset includes information on all offered combination of stops. However, I retain only the service between the main bus terminals. Second, I exclude origins and destinations that are airports. All airports are sufficiently outside cities that consumers are likely to prefer a bus service to the city center. Thirdly, the MFB booking data includes itineraries that involve stopovers, even though I do not observe data on these. This, however, is not a major concern. The German bus market primarily operates as a point-to-point service: the majority of passengers travel directly, meaning few connect to other buses. Buses typically have multiple stops on a line, so the travellers on a given bus may travel very different routes.

DB Emergency timetables and web-crawled itineraries

I construct a dataset of DB service cancellations and expected delays:

Emergency timetables measure the heterogeneity of different routes exposed to the rail strike. DB published emergency timetables for all inter-city (IC) and inter-city express (ICE) lines during the strikes. A route may be served by multiple rail lines and the emergency timetable only includes information on the changed frequency of each DB line (e.g. IC line 31 which operates from Frankfurt to Hamburg via Cologne usually operates every two hours but its service was cancelled entirely during

[29]The author thanks the team of Fernbusse.de for making data on search queries available.

the strike). However, actual travel itineraries are significantly more complex because they often involve stopovers.

To address the issue of stopovers, I gather an additional dataset using an electronic 'web crawler' linked to an online price comparison website for the week April 18-24, 2016.[30] DB has changed timetables twice since 2014, but changes have been minor and after matching with rail lines the data are comparable to the DB service offered in 2014. The web-crawled data includes all travel itineraries for the routes of the dataset in a complete week. A travel itinerary is defined as the specific departure times, stopovers and train numbers a traveller needs to take on a rail journey.

Only the combination of emergency timetables and the web-crawled travel itineraries, allow me to construct the exposure of each route to the rail strike. Using correspondence tables of rail lines and train numbers, I match the emergency timetable data with the crawled dataset. I construct the variables *fraction services cancelled* and *additional travel time* as follows: I construct a variable measuring the trains per hour for the normal and 'treatment' (i.e. strike) period. For example, the route Hamburg–Berlin is served with 1.2 trains per hour during normal operations and 0.2 trains per hour during the strike. Multiplying these numbers by 24 gives the daily number of trains operating on the route; i.e. 28.8 trains during normal operations and 4.8 daily trains during the strikes for Hamburg–Berlin. Using these data, calculating the fraction of services that were cancelled is straightforward (i.e. 0.83 for Hamburg–Berlin). The expected additional travel time travellers have to incur to reach their destination is calculated as the time a traveller has to wait for the next train if his service is cancelled. For simplicity, I assume that the number of daily connections are evenly spaced throughout the day. For example, travellers on a route which is served by one train per hour in normal operations, and only one train every two hours during the strikes had to endure an additional travel time of one hour. I report the calculated fraction of service cancelled and additional travel time in Figure 3 in the data section of chapter 3.

One data limitation, however, remains: the DB emergency timetables do not include information on regional trains. Regional and local trains are likely to have been cancelled in a similar fashion to IC/ICE lines reflecting the local power of the GDL. Since I have no information on the disruption of regional trains, I drop all routes where more than 90 percent of all services offered involve the use of

[30]The web crawling methodology closely follows a small but growing airline literature. See Williams (2013) or Siegert and Ulbricht (2015).

RE and RB trains. This is not a major concern, however, as the large majority of inter-city services is conducted by ICE and IC trains.

The dataset contains all trains, stopovers and travel times for the remaining routes in the sample. Using this information I construct a variable for the frequency in which each route is served per hour. For example, Hamburg–Berlin is served by 1.2 trains per hour on average, while Munich–Berlin is only served by 0.5 trains per hour.

Table 9
Definition of variables used in Equations 1 to 6

Variable:	Definition:
Dependent variables:	
ln ticket sales_{ijt}	Log total MFB ticket sales on route ij on departure date t
ln ticket $\text{sales}_{ijt}^{\text{new}}$	Log total MFB ticket sales to new customers (NC) in the final three days to departure.
Channel variables (channel$_{ij}$):	
Fraction services cancelled	Dummy = 1 if the fraction of DB services cancelled on a route is above the median (i.e. above 63%).
Additional travel time	Dummy = 1 if the additional travel time on a route is above the median (i.e. longer than 78.5 minutes).
Relative travel time	Dummy = 1 if the relative travel time (bus travel time / rail travel time)on a route is below the median (i.e. below ratio 1.64).
Absolute travel time diff.	Dummy = 1 if the absolute travel time difference (bus travel time − rail travel time) on a route is below the median (i.e. shorter than 109.9 minutes).
Bus travel time	Dummy = 1 if the bus travel time on a route is below the median (i.e. shorter than 265 minutes).
Control variables (X_{ijt}):	
School holiday	Dummy = 1 if school holiday in German state (Bundesland). Either origin or destination must be in state.
Public holiday	Dummy = 1 if national or state specific holiday.
Bundesliga (Div. 1)	Dummy = 1 if division 1 football game at origin or destination.
Bundesliga (Div. 2)	Dummy = 1 if division 2 football game at origin or destination.
Munich Oktoberfest	Dummy = 1 if route to or from Munich during Oktoberfest (20/09/2014–03/10/2014).
Stuttgart Wasen	Dummy = 1 if route to or from Stuttgart during Wasen (26/09/2014–12/10/2014).

6.2 Potential transmission channels: additional regression tables

Table 10
Transmission channel: relative travel time difference

	Dep. variable: ln ticket sales$_{ijt}^{new}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Channel × Strike wave 1	-0.0664 (0.0654)	-0.0616 (0.0635)	-0.0683 (0.0628)	-0.176** (0.0755)
Channel × Strike wave 2	0.0124 (0.0627)	0.00719 (0.0608)	-0.000987 (0.0588)	-0.0637 (0.0694)
Channel × Strike wave 3	0.0335 (0.0538)	-0.000881 (0.0535)	0.00898 (0.0542)	0.0752 (0.0718)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.743	0.750	0.754	0.814
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 11
Transmission channel: time delay

	Dep. variable: ln ticket sales$_{ijt}^{\text{new}}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Channel × Strike	-0.101	-0.0650	-0.0605	-0.136
wave 1	(0.0672)	(0.0663)	(0.0647)	(0.0834)
Channel × Strike	-0.0583	-0.0297	-0.0258	-0.153**
wave 2	(0.0612)	(0.0617)	(0.0596)	(0.0730)
Channel × Strike	-0.103*	-0.0807	-0.0744	-0.0348
wave 3	(0.0600)	(0.0574)	(0.0534)	(0.0685)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.743	0.751	0.754	0.814
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 12
Transmission channel: fraction cancelled

	Dep. variable: ln ticket sales$_{ijt}^{\text{new}}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Channel × Strike wave 1	-0.0693 (0.0666)	-0.0199 (0.0655)	-0.0273 (0.0650)	-0.0552 (0.0820)
Channel × Strike wave 2	-0.0896 (0.0652)	-0.0464 (0.0650)	-0.0555 (0.0637)	-0.206*** (0.0712)
Channel × Strike wave 3	-0.0536 (0.0560)	-0.0173 (0.0531)	-0.0346 (0.0568)	0.0189 (0.0729)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.743	0.750	0.754	0.814
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 13
Transmission channel: triple interaction – time delay, bus travel time

	Dep. variable: ln ticket sales$_{ijt}^{new}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Time delay × Strike wave 1	0.172	0.151	0.194	0.159
	(0.216)	(0.207)	(0.206)	(0.212)
Time delay × Strike wave 2	-0.364**	-0.331*	-0.282	-0.315
	(0.181)	(0.177)	(0.179)	(0.204)
Time delay × Strike wave 3	-0.246	-0.204	-0.136	-0.215
	(0.169)	(0.164)	(0.158)	(0.171)
Duration bus × Strike wave 1	0.274***	0.283***	0.274***	0.292***
	(0.0728)	(0.0732)	(0.0715)	(0.0774)
Duration bus × Strike wave 2	0.344***	0.333***	0.322***	0.219***
	(0.0597)	(0.0604)	(0.0596)	(0.0649)
Duration bus × Strike wave 3	0.442***	0.419***	0.403***	0.343***
	(0.0531)	(0.0521)	(0.0488)	(0.0556)
Duration bus × Time delay × Strike wave 1	-0.0488	-0.0581	-0.0878	-0.112
	(0.132)	(0.128)	(0.127)	(0.127)
Duration bus × Time delay × Strike wave 2	0.240**	0.206*	0.172	0.278**
	(0.116)	(0.113)	(0.111)	(0.128)
Duration bus × Time delay × Strike wave 3	0.175*	0.114	0.0856	0.186*
	(0.103)	(0.104)	(0.0955)	(0.104)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.748	0.754	0.757	0.816
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 14
Transmission channel: triple interaction – fraction cancelled, bus travel time

	Dep. variable: ln ticket sales$_{ijt}^{new}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Fraction cancelled × Strike wave 1	0.0323	-0.00689	0.0547	-0.0307
	(0.218)	(0.211)	(0.206)	(0.221)
Fraction cancelled × Strike wave 2	-0.00471	-0.0168	0.0534	-0.00633
	(0.174)	(0.172)	(0.170)	(0.190)
Fraction cancelled × Strike wave 3	-0.329*	-0.323*	-0.224	-0.298
	(0.183)	(0.180)	(0.171)	(0.186)
Duration bus × Strike wave 1	0.254***	0.261***	0.254***	0.271***
	(0.0726)	(0.0731)	(0.0725)	(0.0782)
Duration bus × Strike wave 2	0.404***	0.386***	0.378***	0.266***
	(0.0609)	(0.0611)	(0.0608)	(0.0678)
Duration bus × Strike wave 3	0.432***	0.403***	0.391***	0.337***
	(0.0502)	(0.0489)	(0.0498)	(0.0572)
Duration bus × Fraction cancelled × Strike wave 1	0.0280	0.0212	-0.0135	-0.0316
	(0.131)	(0.128)	(0.125)	(0.133)
Duration bus × Fraction cancelled × Strike wave 2	0.0218	0.00724	-0.0317	0.102
	(0.116)	(0.114)	(0.110)	(0.122)
Duration bus × Fraction cancelled × Strike wave 3	0.204*	0.157	0.123	0.202*
	(0.110)	(0.113)	(0.104)	(0.112)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.748	0.754	0.757	0.816
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 15
Transmission channel: triple interaction – time delay, absolute travel time difference

	Dep. variable: ln ticket sales$_{ijt}^{new}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Time delay × Strike wave 1	0.324	0.392	0.425*	0.363
	(0.270)	(0.260)	(0.256)	(0.272)
Time delay × Strike wave 2	-0.336	-0.265	-0.231	-0.325
	(0.233)	(0.228)	(0.222)	(0.254)
Time delay × Strike wave 3	-0.249	-0.167	-0.118	-0.139
	(0.242)	(0.231)	(0.202)	(0.210)
Absolute duration × Strike wave 1	0.312***	0.377***	0.391***	0.357***
	(0.112)	(0.111)	(0.107)	(0.120)
Absolute duration × Strike wave 2	0.262***	0.285***	0.302***	0.215**
	(0.100)	(0.100)	(0.0978)	(0.0967)
Absolute duration × Strike wave 3	0.312***	0.333***	0.373***	0.366***
	(0.104)	(0.0997)	(0.0865)	(0.0899)
Absolute duration × Time delay × Strike wave 1	-0.102	-0.190	-0.227	-0.140
	(0.157)	(0.153)	(0.152)	(0.171)
Absolute duration × Time delay × Strike wave 2	0.271*	0.197	0.156	0.358**
	(0.144)	(0.140)	(0.136)	(0.165)
Absolute duration × Time delay × Strike wave 3	0.247*	0.168	0.106	0.120
	(0.139)	(0.135)	(0.120)	(0.135)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	8300	8300	8300	8000
R^2	0.773	0.783	0.787	0.844
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 16
Transmission channel: triple interaction – fraction cancelled, absolute travel time difference

	Dep. variable: ln ticket sales$^{new}_{ijt}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Fraction cancelled × Strike wave 1	0.0710 (0.269)	0.104 (0.262)	0.196 (0.254)	0.0554 (0.280)
Fraction cancelled × Strike wave 2	0.141 (0.237)	0.128 (0.231)	0.239 (0.225)	0.139 (0.245)
Fraction cancelled × Strike wave 3	-0.557** (0.231)	-0.555** (0.222)	-0.391** (0.193)	-0.444** (0.199)
Absolute duration × Strike wave 1	0.235** (0.110)	0.297*** (0.110)	0.328*** (0.109)	0.281** (0.116)
Absolute duration × Strike wave 2	0.412*** (0.107)	0.413*** (0.104)	0.452*** (0.101)	0.359*** (0.107)
Absolute duration × Strike wave 3	0.225** (0.0910)	0.226*** (0.0833)	0.302*** (0.0761)	0.297*** (0.0788)
Absolute duration × Fraction cancelled × Strike wave 1	0.0311 (0.156)	-0.0495 (0.153)	-0.116 (0.148)	0.0170 (0.162)
Absolute duration × Fraction cancelled × Strike wave 2	-0.0227 (0.147)	-0.0580 (0.143)	-0.136 (0.136)	0.0724 (0.153)
Absolute duration × Fraction cancelled × Strike wave 3	0.396*** (0.134)	0.355*** (0.133)	0.238** (0.111)	0.261** (0.119)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	8300	8300	8300	8000
R^2	0.773	0.783	0.787	0.845
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 17
Transmission channel: triple interaction – time delay, relative travel time difference

	Dep. variable: ln ticket sales$^{new}_{ijt}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Time delay × Strike wave 1	-0.159	-0.0474	-0.0459	0.174
	(0.298)	(0.295)	(0.284)	(0.339)
Time delay × Strike wave 2	-0.227	-0.177	-0.171	-0.108
	(0.249)	(0.251)	(0.250)	(0.257)
Time delay × Strike wave 3	0.0507	0.0882	0.112	0.0328
	(0.293)	(0.284)	(0.253)	(0.299)
Relative duration × Strike wave 1	-0.137	-0.0949	-0.106	-0.0715
	(0.132)	(0.132)	(0.127)	(0.145)
Relative duration × Strike wave 2	0.0113	0.00686	-0.00242	-0.0768
	(0.105)	(0.108)	(0.109)	(0.105)
Relative duration × Strike wave 3	0.156	0.150	0.143	0.114
	(0.128)	(0.126)	(0.110)	(0.125)
Relative duration × Time delay × Strike wave 1	0.187	0.0664	0.0465	-0.0311
	(0.181)	(0.177)	(0.171)	(0.191)
Relative duration × Time delay × Strike wave 2	0.188	0.121	0.0957	0.161
	(0.158)	(0.157)	(0.158)	(0.178)
Relative duration × Time delay × Strike wave 3	0.0506	-0.0158	-0.0608	0.00329
	(0.167)	(0.162)	(0.147)	(0.178)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	8300	8300	8300	8000
R^2	0.770	0.780	0.784	0.842
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 18
Transmission channel: triple interaction – fraction cancelled, relative travel time difference

	Dep. variable: ln ticket sales$_{ijt}^{\text{new}}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Fraction cancelled × Strike wave 1	-0.0610 (0.275)	-0.0537 (0.267)	-0.0368 (0.262)	0.0537 (0.305)
Fraction cancelled × Strike wave 2	0.232 (0.259)	0.207 (0.252)	0.234 (0.249)	0.364 (0.270)
Fraction cancelled × Strike wave 3	-0.119 (0.263)	-0.178 (0.248)	-0.114 (0.241)	-0.226 (0.274)
Relative duration × Strike wave 1	-0.112 (0.118)	-0.0962 (0.116)	-0.100 (0.118)	-0.101 (0.124)
Relative duration × Strike wave 2	0.156 (0.117)	0.133 (0.114)	0.133 (0.114)	0.0637 (0.116)
Relative duration × Strike wave 3	0.0952 (0.102)	0.0628 (0.0967)	0.0739 (0.0946)	0.0409 (0.107)
Relative duration × Fraction cancelled × Strike wave 1	0.0896 (0.169)	0.0235 (0.162)	0.00540 (0.159)	-0.0230 (0.173)
Relative duration × Fraction cancelled × Strike wave 2	-0.0938 (0.159)	-0.126 (0.154)	-0.150 (0.153)	-0.0977 (0.172)
Relative duration × Fraction cancelled × Strike wave 3	0.0974 (0.154)	0.0781 (0.144)	0.0296 (0.139)	0.0963 (0.164)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	8300	8300	8300	8000
R^2	0.769	0.780	0.784	0.842
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 1. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

6.3 Robustness and additional results

Table 19
Robustness: continuous dependent variable: ln(*bus travel time*)

	Dep. variable: ln ticket sales			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Treated × Strike wave 1	0.906*** (0.204)	0.975*** (0.206)	0.994*** (0.202)	0.991*** (0.222)
Treated × Strike wave 2	1.821*** (0.160)	1.735*** (0.161)	1.752*** (0.156)	1.576*** (0.191)
Treated × Strike wave 3	2.228*** (0.168)	2.095*** (0.169)	2.092*** (0.156)	1.992*** (0.183)
Treated × Post	1.513*** (0.108)	1.427*** (0.103)	1.416*** (0.101)	1.454*** (0.118)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	26832	26832	26832	26488
R^2	0.876	0.879	0.881	0.913
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 20
Robustness: treatment absolute travel time difference

	Dep. variable: ln ticket sales			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Treated × Strike wave 1	0.0293	0.0445	0.0542	0.0374
	(0.0488)	(0.0471)	(0.0451)	(0.0530)
Treated × Strike wave 2	0.130***	0.134***	0.145***	0.154***
	(0.0421)	(0.0405)	(0.0386)	(0.0416)
Treated × Strike wave 3	0.219***	0.202***	0.225***	0.238***
	(0.0425)	(0.0426)	(0.0388)	(0.0455)
Treated × Post	0.140***	0.147***	0.177***	0.179***
	(0.0276)	(0.0256)	(0.0247)	(0.0274)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	26832	26832	26832	26488
R^2	0.871	0.874	0.878	0.910
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 21
Robustness: treatment routes from or to East German cities

	Dep. var.: ln ticket sales$^{new}_{ijt}$		
	(1) Basic DD	(2) DD +trend	(3) DD + controls
Channel × Strike	0.113	0.127	0.135
wave 1	(0.128)	(0.125)	(0.130)
Channel × Strike	0.0655	0.0515	0.0771
wave 2	(0.117)	(0.0941)	(0.125)
Channel × Strike	0.163**	0.183*	0.215**
wave 3	(0.0794)	(0.0968)	(0.106)
Add. Controls			✓
Route - trend		✓	
Origin - trend			✓
Destination - trend			✓
Day FEs	✓	✓	✓
Route FEs	✓	✓	✓
Observations	15600	15600	15600
R^2	0.721	0.736	0.728
Clustered SEs	✓		✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level.)

Table 22
Robustness: excluding Berlin

	Dep. variable: ln ticket sales			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Treated × Strike wave 1	0.172***	0.187***	0.195***	0.235***
	(0.0446)	(0.0457)	(0.0445)	(0.0487)
Treated × Strike wave 2	0.351***	0.325***	0.334***	0.355***
	(0.0345)	(0.0342)	(0.0328)	(0.0427)
Treated × Strike wave 3	0.413***	0.387***	0.396***	0.418***
	(0.0373)	(0.0370)	(0.0342)	(0.0396)
Treated × Post	0.283***	0.264***	0.277***	0.286***
	(0.0217)	(0.0211)	(0.0205)	(0.0248)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	21672	21672	21672	20984
R^2	0.824	0.828	0.832	0.879
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 23
Robustness: dependent variable ln(*total ticket sales*); excluding post-strike period

	Dep. variable: ln ticket sales$^{new}_{ijt}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
Channel × Strike wave 1	0.131*** (0.0462)	0.148*** (0.0453)	0.131*** (0.0436)	0.128*** (0.0464)
Channel × Strike wave 2	0.291*** (0.0356)	0.277*** (0.0349)	0.258*** (0.0344)	0.225*** (0.0394)
Channel × Strike wave 3	0.387*** (0.0377)	0.355*** (0.0376)	0.330*** (0.0328)	0.326*** (0.0396)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	15600	15600	15600	15400
R^2	0.881	0.885	0.888	0.917
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 24
Robustness: including two days before and after each strike, and intermediate period

	Dep. variable: ln ticket sales			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Treated × Strike wave 1	0.134*** (0.0378)	0.158*** (0.0377)	0.159*** (0.0373)	0.164*** (0.0410)
Treated × Strike wave 2	0.306*** (0.0287)	0.301*** (0.0294)	0.300*** (0.0288)	0.276*** (0.0355)
Treated × Strike wave 3	0.386*** (0.0294)	0.361*** (0.0297)	0.355*** (0.0273)	0.354*** (0.0330)
Treated × Post	0.255*** (0.0169)	0.242*** (0.0169)	0.229*** (0.0158)	0.260*** (0.0185)
Add. Controls		✓	✓	✓
Origin - trend			✓	✓
Destination - trend			✓	✓
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	33384	33384	33384	32956
R^2	0.877	0.880	0.882	0.914
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 25
Robustness: excluding within-German flights

	Dep. variable: ln ticket sales$_{ijt}^{new}$			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.-Day FE
Channel × Strike wave 1	0.235*** (0.0632)	0.252*** (0.0635)	0.234*** (0.0625)	0.273*** (0.0697)
Channel × Strike wave 2	0.425*** (0.0526)	0.406*** (0.0526)	0.385*** (0.0526)	0.333*** (0.0664)
Channel × Strike wave 3	0.458*** (0.0476)	0.427*** (0.0471)	0.396*** (0.0458)	0.371*** (0.0544)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	14800	14800	14800	14600
R^2	0.740	0.746	0.749	0.811
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)

Table 26
Robustness: excluding return ticket bookings

	Dep. variable: ln ticket sales			
	(1) Basic DD	(2) DD + controls	(3) DD + trend	(4) Orig.-, Dest.- Day FE
treated × Strike wave 1	0.153***	0.159***	0.162***	0.152***
	(0.0375)	(0.0384)	(0.0375)	(0.0410)
treated × Strike wave 2	0.355***	0.341***	0.345***	0.314***
	(0.0296)	(0.0299)	(0.0296)	(0.0392)
treated × Strike wave 3	0.367***	0.350***	0.351***	0.337***
	(0.0313)	(0.0315)	(0.0295)	(0.0340)
treated × Post	0.255***	0.243***	0.244***	0.255***
	(0.0170)	(0.0169)	(0.0166)	(0.0193)
Add. Controls		✓	✓	
Origin - trend			✓	
Destination - trend			✓	
Day FEs	✓	✓	✓	
Route FEs	✓	✓	✓	✓
Origin-Day FEs				✓
Destination-Day FEs				✓
Observations	26832	26832	26832	26488
R^2	0.873	0.875	0.877	0.909
Clustered SEs	✓	✓	✓	✓

Notes: Estimated coefficients from Equation 2. Standard errors in parentheses, clustered at the route level (166 clusters). ***/**/* indicate significance at the 1%/5%/10% level. Column 4 refers to the inclusion of γ_{it} and γ_{jt} – origin- and destination-day specific fixed effects.)